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Slangsh: a Dictionary of Worldwide Slangs

Master's Thesis
Espoo, May 26, 2016

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ABSTRACT OF
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Currently, people use different online services (i.e., websites and mobile applications) for different language learning purposes. On the hand, online businesses use usually use different approaches and techniques to process a massive amount of text in different languages, in order to analyze users' feedback and opinions regarding different entities such as products, movies, or pictures. Although the available online language learning platforms and opinion mining techniques are useful in different cases, they still suffer from some limitations related to slangs in different languages. Slangs (plural of slang) are any informal words or idioms used by people in different languages and countries. These slangs are continuously developed, especially in dense social networks and communities. In addition, people also use slangs to communicate on online services (e.g., Facebook[a]) as well as to write reviews on different websites. Accordingly, learning about specific language's slangs would be useful for many people. The current problems related to slangs are twofold: with people, and with online businesses. For people, there is no any comprehensive online dictionary to learn about worldwide slangs. On the other hand, online businesses have some challenges to understand the semantics (e.g., sentiments and contexts) behind the texts being exchanged on their platforms. Both people and online businesses face the problem of inaccurate translation of slang using current available online translation services. Therefore, in this thesis we propose, design, and develop a novel solution with main objective and vision to build the largest online knowledge base of slangs. In order to achieve this objective, we used different approaches and methodologies both theoretical and empirical. We conducted a literature review in the sentiment analysis domain. In addition, we made different personal interviews as well as an online survey to validate our assumptions and facts about slang development in different languages and countries. Moreover, we followed the action research approach and developed an Android application to evaluate our proposed solution (Slangsh). We found out that Slangsh would have a good potential to build a comprehensive knowledge base of worldwide slang as well as to address the problem of the inaccurate translation of slangs in different languages. The main contribution of this thesis is to design, develop, and propose a novel solution that is based on crowdsourcing and collaborative learning to collect slangs from different languages and countries.

[a]http://facebook.com/

Keywords:	knowledge base, slang dictionry, crowdsource, mutlilingual, sentiment analysis, opinion mining, collaborative learning
Language:	English

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Mahmoud Khodier

Abbreviations and Acronyms

Slangsh	This is the name of the final product (currently is only an Android Application)
Slang	Represents any informal word or phrase used by people in specific language, country, or city.
Slangs	Plural of Slang
SVM	Support Vector Machine is a technique used in machine learning (supervised learning) for classification.
TS	Translation Service (e.g. Google translate).
App	Refers to a mobile application (e.g. Android app, or iOS app)
User	Used to refer to the user of the Android application
Author	Used in the literature review to refer to researcher, and used in the proposed solution to refer to the user who posted a slang on the Android app.
API	Application Programming Interface represents the back-end service responsible for storing, retrieving, and processing the data.

Contents

Chapter 1

Introduction

1.1 Background and Motivation

Currently, there are some online services (i.e., websites and mobile applications) that could be used to learn about different languages in the world such as English, Spanish, and Arabic. For instance, people use Duolingo[1] to learn about new languages through interactive online materials and lessons. In addition, people used UrbanDictionary[2] to learn about slangs (the majority is English), before it turned out to focus on any word or idiom whether it is a slang or not. Slangs (plural of slang) are any informal words or idioms used by people in different languages and countries (e.g., "so gross" which is a slang idiom in English that means "very disgusting", or "Donkey's year" which means "a very long time"). Finally, people use different online translation services to translate any text to a specific language. The most popular online translation service is Google Translate[3]. Although the current available online services are still useful for different language learning purposes, they have some limitations related to slangs in different languages. Accordingly, when people learn a new language using available solutions, they mostly learn only about the basic and standard formal language, but not about language slang. In addition, there is no available rich dictionary that contains slangs in all languages and their meaning.

On the other hand, online businesses such as Facebook[4] and Google[5] usually use different approaches and techniques to process a massive amount of text in different languages, in order to analyze users' feedback and opinions regarding different entities such as products, movies, or pictures. This process is called

[1] https://www.duolingo.com/
[2] http://www.urbandictionary.com/
[3] http://translate.google.com/
[4] http://facebook.com/
[5] https://www.google.com

sentiment analysis or opinion mining. Approaches used in sentiment analysis includes: machine learning, machine translation, and hybrid techniques; however, available dictionary-based approach used for opinion mining and sentiment analysis has some limitations in multilingual settings in general and slangs in specific. In other words, there is no structured and comprehensive dictionary that maps "words/idioms used by people in different languages and countries" to sentiments in different contexts. The current available sentiment lexicons are mostly rich only in English, but not in other languages[2, 14, 19]. Therefore, many research studies, aimed to perform sentiment analysis in multilingual settings, used machine translation to translate specific text in a given language (e.g., German) to English. Then, the sentiment analysis is performed over the English text using the rich English sentiment lexicon; however, the machine translation approach for sentiment analysis has some limitations[2, 13, 15]. In addition, the translations of slangs using current available online services (e.g., Google Translate) are usually either inaccurate or provide wrong translations.

Slangs are continuously developed, especially within social networks and communities (e.g., social media websites, schools and universities). In addition, slangs are different depending on their context and might create misunderstandings among nations as well as among generations [6]. People usually use slangs to communicate during their daily life. Moreover, they also use slangs to communicate on online services (e.g., Facebook) as well as to write reviews on different websites about different entities (e.g., picture, video, or product)[17]. Accordingly, these slangs have some attached sentiments and used in different contexts. Therefore, it would be challenging for online businesses to understand the semantics behind some of the text being exchanged on their platforms, especially that sentiment lexicons are not rich in most of the languages. Understanding the semantics of the text is important if these businesses use dictionary-based approach to perform the sentiment analysis and the opinion mining over a text in different languages. Accordingly, a structured dictionary of slangs in different languages attached with their sentiments would be useful for analyzing people's opinion.

1.2 Objectives and Scope

To our best knowledge, there is no comprehensive dictionary for slangs that are being used in different languages and countries. Moreover, even if there are some available websites and mobile applications that contain slangs in specific languages, these slangs are not labelled with any sentiment or context. Therefore, our main objective and contribution in this research project is to design, develop, and propose a solution that could be used to build the largest online and centralized knowledge base of world-wide slangs. Such a comprehensive knowledge base of world-wide slangs would be useful in different real-life applications. First, we want to help people (e.g., international students, travelers, language learners) to learn about slangs in different languages and countries. Second, we want to enable online businesses to understand the semantics of the text being exchanged on their platforms. By semantics, we mean both sentiments and contexts attached to slangs. This will help these businesses to improve their recommendations as well as their revenues. Third, we want to face the problem of the inaccurate translations of slangs. Finally, we would like to achieve all these goals by proposing a web and mobile application that is based on crowdsourcing and collaborative learning. In other words, users of the solution will be responsible for generating the content as well as ensuring content quality. Accordingly, we want to include some incentives for people to download and use our proposed solution.

We have limited the scope of this study to focus on some specific aspects. First, we want to study and validate some facts regarding slang development in different countries and languages. Second, we need to design and propose a novel solution to build a comprehensive dictionary of world-wide slangs. Third, we want to study the literature of the sentiment analysis in multilingual settings and consider some limitations of this domain in our proposed solution. Finally, we want to implement and evaluate the solution against our ultimate goals and objectives.

1.3 Methodologies and Results

In order to achieve our main objective, we used different approaches in this thesis. We used interviews as a qualitative method to validate our assumptions as well as to collect some facts about slangs in different languages and countries. Second, as the interviews were on a small scale of people, we used an online survey as a quantitative method to validate the assumptions as well as the facts collected from the interviews and the literature review. The online survey was conducted on a large number of individuals and this ensures more reliability for the validation of collected data. Third, as one of our goals is to consider the sentiments of slangs, we wanted to identify current challenges in the sentiment analysis domain. Therefore, we followed a theoretical study and reviewed the literature of sentiment analysis on online digital communities. Fourth, we followed the action research approach and developed an Android application to test and evaluate our proposed solution. Finally, for the evaluation, we used their party tools such as Google Play Store[6] and Google Analytics[7] to collect and analyze different statistics.

Based on the evaluation, we found that our proposed solution (Slangsh) could have a good potential to build a comprehensive knowledge base of worldwide slangs

[6] http://play.google.com/
[7] http://analytics.google.com/

labelled with different useful information such as definitions, sentiments, and contexts. This would be useful for people to learn about slangs in different languages as well as for online business to understand the semantics of slangs being textually exchanged on their platforms. In addition, we compared the accuracy of slang translation using Slangsh against Google Translate and the result showed that Slangsh can provide more accurate translation than Google. We have also concluded some limitations and challenges that we should work on in the future such as improving the usability, and adding more incentives for crowdsourcing.

1.4 Structure of the Thesis

This thesis is organized as follows: Chapter 2 provides more details about our motivation to work on Slangsh by reporting the results of the interviews and the online survey regarding slang development in different languages and countries. Chapter 3 presents a literature review about sentiment analysis and conclude some challenges and limitations in this domain. Chapter 4 presents the proposed solution and our design decisions. Chapter 5 outlines different technologies and tools we have used to implement our solution, and Chapter 6 describes how we evaluated our solution, discusses user analytics, and presents the challenges and the limitations in our solution. Finally, Chapter 7 discusses and concludes the outcomes and challenges in this research project.

Chapter 2

Why Slangsh?

The main objective from Slangsh is to build the largest online dictionary of worldwide slang on which each slang is labelled with language, country, city, age range, sentiments of slang, contexts where the slang is being commonly used, and finally (definitions and synonyms in different languages). Slangsh is based on crowdsourcing and collaborative learning on which people can share their native slang, and also learn about other slangs in different languages. The importance of Slangsh is for people to learn and for online businesses to understand their users. This chapter is organized as follows: Section 1 is about our motivation to work on slangsh. Section 2 is about how we validated the value proposition of Slangsh with people, and section 3 states how people are currently learning about slang in different languages. Finally, section 4 discusses how could we differentiate ourselves from existing similar solutions.

2.1 Motivation

Based on the personal experience in learning new languages, direct interviews with people from different countries (presented in Section 2.2.1), and a literature review (presented in Chapter 3), we found that there is an opportunity for Slangsh to fulfill some needs and solve some problems as follows:

- Enable people (e.g., language learners, travellers, or immigrants) to learn about the informal ways of speaking in different languages and countries. When people learn a new language, they mostly learn only about the basic and standard formal language, but not about about language slang.
- For online businesses (e.g., Google, Facebook, eBay, Amazon, or Twitter) to understand the semantics of texts being exchanged through their platforms given that the massive amount of text that is being exchanged daily contains

both slang and non-slang words/idioms. In turn, businesses can improve their recommendations as well as their revenues if they could understand the attached sentiments and contexts with slang words and idioms.

- Inaccurate translation of slang in different languages which is a current problem on online translation services (e.g., Google translate[1]).

2.2 Would people really need Slangsh?

We found that interviews would best fit to validate the value proposition of Slangsh. In interviews, we had the opportunity to communicate directly with people from different countries who are speaking different languages and ask them some questions about their native slangs. The main objective from the interviews was to conduct some observations and conclude some facts about slang in different languages and countries. However, as the scale of the interviews was not big enough, we have had to validate the conducted observations by an online survey.

2.2.1 Interviews

We have interviewed eight persons from eight different countries. The countries are: Germany, Egypt, Bangladesh, Colombia, France, Pakistan, Greece, and Mexico. The interviewees are both males and females, and there was a diversity of young and middle-aged people. All interviews reported that they use slangs in their daily life as well as it is very common that they use slangs for online textual communication. Hence, the last claim has been also reported by a research study [17] in which the authors mentioned that people use slangs to write reviews about products on online platforms to express their opinions. Moreover, the interviewees have mentioned that slangs are different inside the same country based on specific city and age, as well as there are different slangs in different countries, even if these countries speak the same language (e.g., Spanish for Colombia and Mexico). The questions asked during the interviews are listed in Appendix A. Fig. 2.1 provides a sample of responses collected from some interviewees.

Most of the interview questions were yes/no questions. However, there was a basic question that allowed the interviewees to speak freely and tell us, in detail, about their slang. This question is "Do you have slangs in your language/country? Tell us more about that". Based on this question, we were able to conduct some important observations. A list of core observations that have been conducted from the interviews collected from could be summarized as follows:

- Slangs are different for each age generations.

[1]https://translate.google.com

Figure 2.1: Sample Feedback from the Interviewees

- People use slangs in daily life communications.
- Slangs in specific country are different over cities.
- Slangs are also different in different countries that use the same language (e.g., Mexico and Spain).
- People use slangs for online communications.
- When people learn a new language, they only learn standard words and phrases, but not slangs.

These facts demonstrate how important it would be to build a comprehensive and centralized knowledge base of slangs in different languages and countries. However, these facts have been obtained through few interviews. Therefore, it was important to validate these facts on a larger sample of individuals using an online.

2.2.2 Online Survey

The main objective of using an online survey is to validate the observations and problems identified during the interviews, as well as the literature review (presented in Chapter 3). The survey allowed us to validate the collected data from the interviews and the literature on a large sample of users. The questions asked in the survey are listed in Appendix B. In order to get responses for the survey, we distributed it on different social media channels and websites such as Linkedin[2], Google+[3], and Reddit[4]. For the first two channels, we browsed and distributed the survey to groups and communities that are interested in linguistics.

Demographic and Context-related Information

Our focus for this survey is to validate our assumptions as well as the observations obtained from the interviews and the literature review. Accordingly, we did not care much about people's demographic information (e.g., gender or age). We only asked respondents to mention their home country and native language. This information is important for us as our questions are around slangs in different languages and countries.

The Sample

In four days, we got 66 responses for our online survey. The respondents are from 30 different countries and speak 22 different languages. Exact information about respondents' home countries and native languages are listed in Appendix C.

Analysis of the Survey

The analysis of the survey's responses has approved and confirmed the observations we collected during the interviews (in section 2.2.1) and the literature review (in Chapter 3). First, we asked the respondents if they have slang in their language and country. Fig. 2.2 states that 98.5% of respondents have slangs in their native language. Second, we asked the respondents if they are using slangs in their daily life. Fig. 2.3 shows that 86.4% of respondents are using slangs in their daily life. Third, we asked them if they are using slangs while communicating online (e.g., chatting, writing on social media channels). It was not a surprise that we got the same percentage (i.e., 86.4%) as the second question (slangs usage per daily life).

Fourth, we asked the respondents how often do they use slangs during their daily life or for online communication. Fig. 2.4 shows the percentage of the time spent by the respondents using slangs in their daily life either for online or offline communications. The majority of responses (42.4%) state that the respondents spend up to 25% of their time during the day using slangs. In addition, 36.4% of the respondents stated that they spend up to 50% of their time during the day using slangs, and finally around 20% of the respondents mentioned that they spend

[2]https://www.linkedin.com

[3]http://plus.google.com/

[4]https://www.reddit.com/

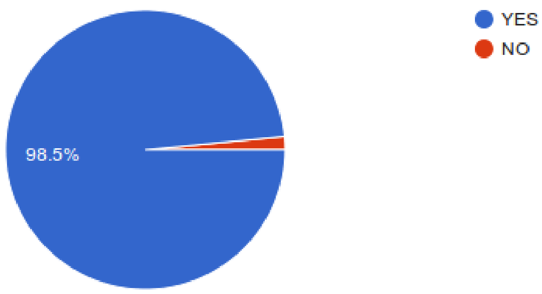


Figure 2.2: Slangs/Languages

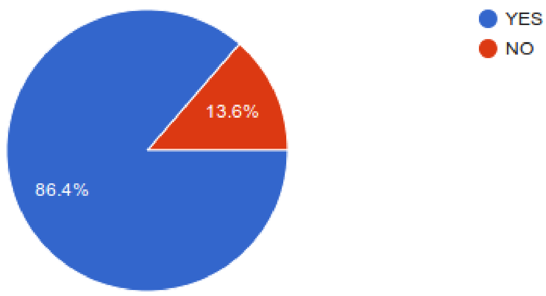


Figure 2.3: Slangs/Daily Life

more then 50% of their time during the day using slangs. These statistics are very important and have useful implications. Even though they show that people use slangs with different percentages during their day, we can conclude that 57.6% of the respondents use slangs more than 25% of their time during the day. This is relatively high percentage and shows how much slangs used in people everyday's life.

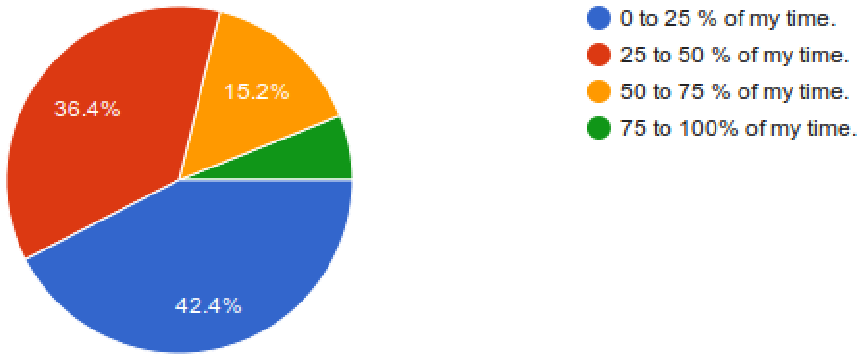


Figure 2.4: Usage of Slangs in Daily Communications (Online/Offline)

Fifth, we asked the respondents if slangs in their country are the same in different cities. Fig. 2.5 shows that 93.9% of the respondents confirmed that different cities use different slangs within the same country. Sixth, we asked the respondents if slangs in their country are different based on people's age. 92.4% of the respondents confirmed that people use different slangs based on their age as shown in Fig. 2.6.

Seventh, we asked the respondents if they would be familiar with slangs from

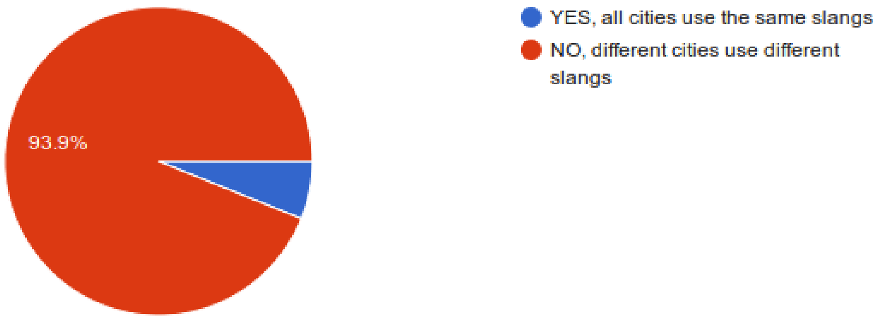


Figure 2.5: Usage of Slangs in Cities

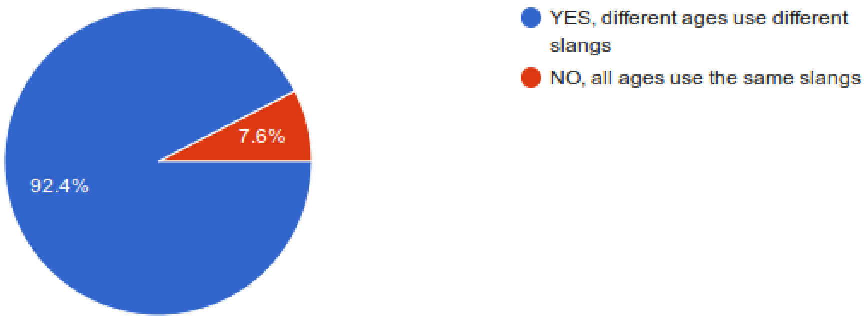


Figure 2.6: Relation between Slangs and Ages

other countries that speak their native languages (e.g., Mexico and Spain both speak Spanish). 54.5% of the respondents mentioned that they are not sure, while 27.3% mentioned that they will not be familiar with slangs from other countries, even if they speak the same language. Finally, only 18.2% of the respondents mentioned that they would be familiar with with slangs from other countries that speak their native languages. Fig. 2.7 shows these statistics.

Eighth, we asked the respondents if they learn about slangs when they learn a new languages (e.g., attend classes, watch videos, or using web or mobile applications). Fig. 2.8 shows the responses from the respondents. 59.1% of the respondents mentioned that they only learn about basic words and idioms, while 40.9 of the respondents mentioned that they learn about both basic words and idioms as well as slangs. It is worth mentioning that we got direct questions from some respondents regarding this question whether we mean about learning slangs during classes or self-learning. Accordingly, we rephrased the question after

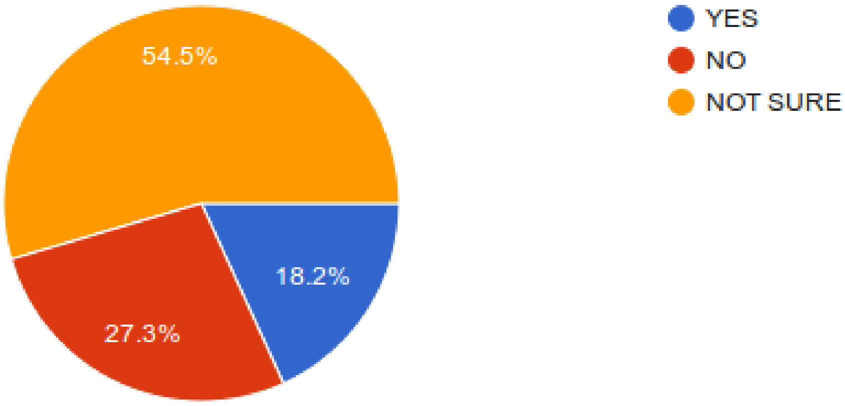


Figure 2.7: Familiarity with Slangs from Other Countries

receiving around 30 responses.

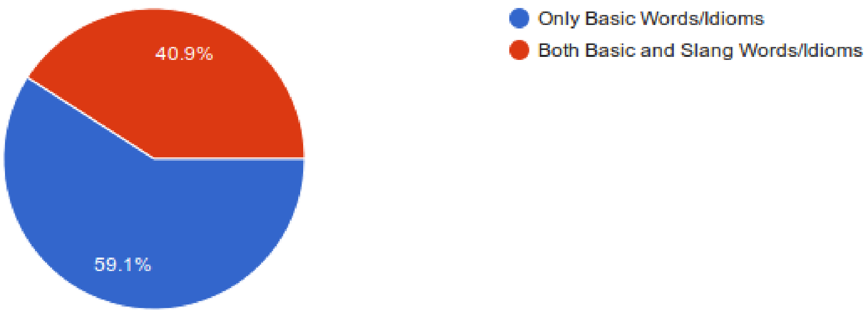


Figure 2.8: Learn Slangs while Learning a New Language

Finally, we asked the respondents a very important question about accuracy of available online translation services (e.g., Google Translate) to translate slangs. Fig. 2.9 states the responses from the respondents. As expected, no one mentioned that they ever got accurate translation for a slang using available online translation services. 47% mentioned that the translation of slangs are always inaccurate using available online translation services. 34.8% of the respondents mentioned that sometimes the translation of slangs are inaccurate. Interestingly, 18.2% of the respondents mentioned that they never translated a slang.

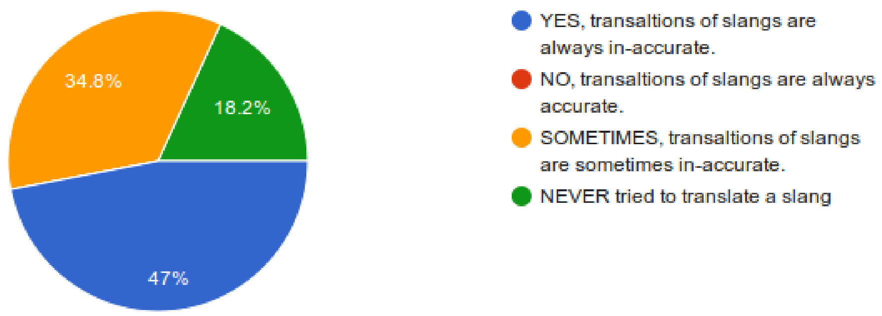


Figure 2.9: Accuracy of Slang Translation

2.3 Slangsh vs. Existing Solutions

There are some existing solutions that could be used for different language learning purposes, and also that could be compared and compete with Slangsh either directly or indirectly. Urban Dictionary[5] is a very popular and it has a rich base of English words and idioms, but it is not really rich with slangs from other languages. Although Urban Dictionary offers a responsive web application, Urban Dictionary's native mobile app has not been updated since April, 2013. They also stated explicitly on the description of their mobile app that people can define any word either slang or non-slang, and finally they do not consider the sentiment or the context of the word being defined. Additionally, Duolingo[6] and Google Translate[7] could be considered as indirect competitors. Duolingo enables people to learn a new language; however the focus is not on learning slang. On the other hand, Google introduced translate community to enable people add translations with their native languages. All these solutions make a great job, but Slangsh can differentiate itself from these solutions as it targets slang in different languages, and it considers labelling slang with (language, country, city, age, sentiments, domains/contexts, and definitions/synonyms in different languages). The main objective is to build a centralized and comprehensive knowledge base of worldwide slang.

Companies currently do not have an integrated and comprehensive solution for slangs in different countries. In other words, there is no solution that answer the following questions: what do people in different (countries/languages) say or text on their daily life? in which context? what does this text mean? and what

[5]http://www.urbandictionary.com/
[6]http://www.duolingo.com/
[7]http://translate.google.com/

are the attached sentiments and contexts with these texts? Slangsh will do that. However, it is worth mentioning that some companies started to care about these issues (slangs and sentiments) in different ways:

- Google[8] has introduced Google Translate Beta on which they ask people to introduce their own native translations.

- Facebook[9] has updated their like button to include more emotions (e.g., Angry, Love ...etc).

The first company cares about how people actually speak or text. On the other hand, the later company cares about how people actually feel. Slangsh will care about and integrate both (text and sentiment). Fig. 2.10 provides a comparison between Slangsh and current existing solutions, and it shows how could Slangsh differentiate with new features.

[8] http://www.google.com
[9] http://www.facebook.com

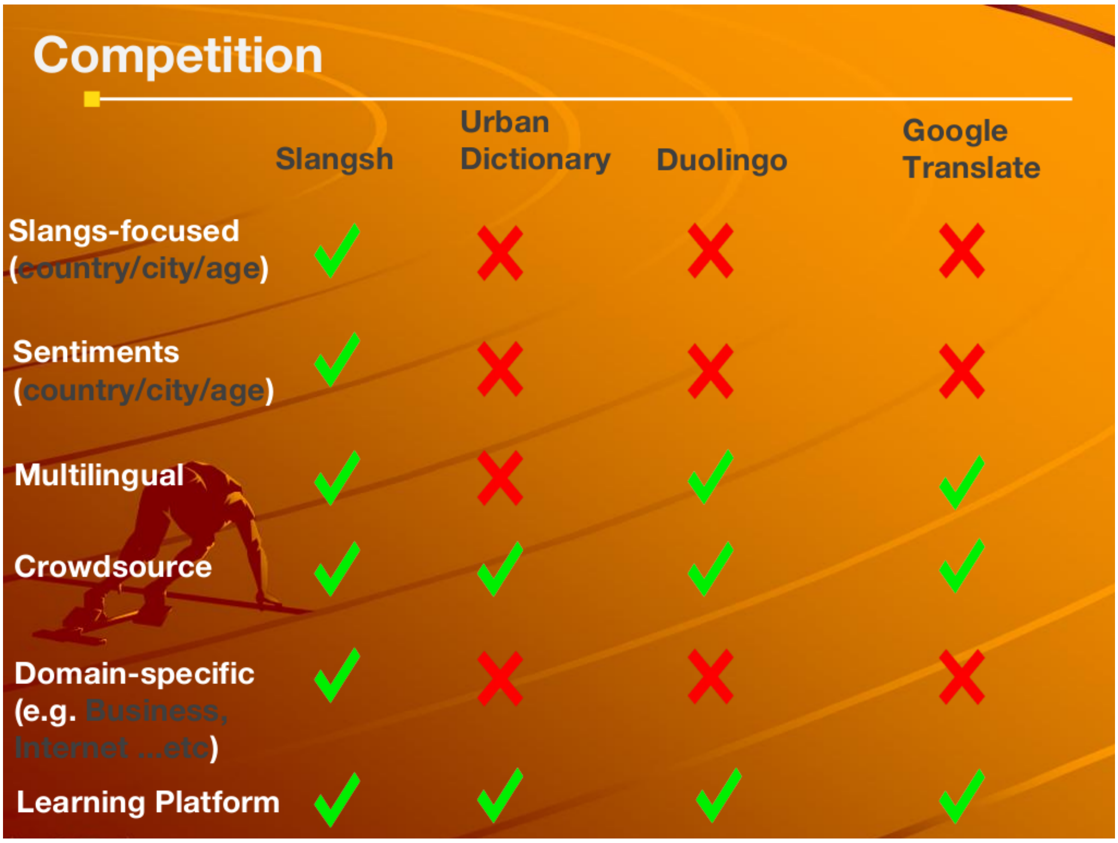


Figure 2.10: Competitor Analysis

Chapter 3

Sentiment Analysis: a Survey

In Slangsh, one of our goals is to consider and solve some of the limitations in the sentiment analysis domain. Therefore, it was necessary to review the literature of sentiment analysis in multi-language settings, so that we can identify current challenges and issues. Then, we can approach some of these challenges by our proposed solution, in order to improve the sentiment analysis process.

Sentiment analysis is currently an important process for businesses that enables them to extract feedback and opinions of their customers regarding a specific entity (e.g., product) in order to help them improve user experience as well as their revenues. Notably, online services (e.g., social networks and e-commerce) support many languages for different users from different countries around the world. The amount of textual data produced in different languages is so massive that it introduces many challenges for these services wanting to perform sentiment analysis on the data, especially if this data contains slangs. In light of this, this survey reviews the literature and mainly focuses on the challenges and issues of multilingual sentiment analysis (MLSA). Accordingly, the main contribution of this survey is that it classifies different research literature related to MLSA based on techniques, data sets, and languages used in the research experiments. In addition, the survey presents challenges and issues in MLSA domain, and directions for future research.

3.1 Introduction

Sentiment analysis and opinion mining are two different terms that are being used interchangeably. Both terms refer to the process of studying and capturing people's opinions, sentiments, and attitudes towards a specific entity [18]. This entity could be a person, product, service, or any kind of published content (e.g., a post of an online social network or a book on an e-commerce website). Sentiment analysis is very important to businesses as it helps them better understand their customers and therefore improve their offerings, user experience, as well as their overall revenue. However, with so many published opinions to source from, the analysis process is challenging and needs to be automated especially when these opinions are published on websites that support many languages (e.g., English, French, Arabic, Spanish).

Digital communities are online services that provide people around the world with different communication facilities. The majority of online digital communities allows their users to use textual communications and some of these platforms support multiple languages as well. These communications are described as an interaction between different entities such as persons or objects. For instance, both Alice and Bob have an account on Facebook[1] and they are able to text each other via the instant messaging service provided by the platform. Alice also is able to comment on objects posted by Bob on Facebook and these objects could be textual or graphical content. Additionally, Bob usually does online shopping on Amazon[2] and because he cares about the quality of its service, he is always providing textual feedback for different objects (e.g., purchased products or sellers).

The volume of text generated on digital communities is massive. Although the communication and interaction processes might seem very smooth for end-users, it is very complex for businesses (e.g., Facebook and Google[3]) to analyze these texts in order to extract people's opinion of different objects (e.g., persons, products, or content), especially if these texts contains slang words or idioms. Despite this problem, analysis of opinions is very helpful for businesses because they are able to enhance user experience and their recommendation systems. For instance, Facebook recommends better ads or content to the users based on those users' opinions that are automatically identified from the text they share on the service. Fig. 3.1 provides a conceptual model that depicts the importance of sentiment analysis and opinion mining in digital communities.

The model shows that each type of digital community produces a massive volume of multilingual text that might describe and include opinions about different entities. This text could contain standard words/idioms, as well as slang words/idioms. An opinion mining engine is responsible for analyzing these texts either related to a single customer (e.g., user on an online social network) or cluster of customers, and in turn state whether the overall opinion related to specific entity is positive, negative, or neutral. These results will be fed into a recommendation engine that is responsible for recommending content to customers based on their interests and previous opinion. This would improve the overall user experience

[1] `www.facebook.com`
[2] `www.amazon.com`
[3] `www.google.com`

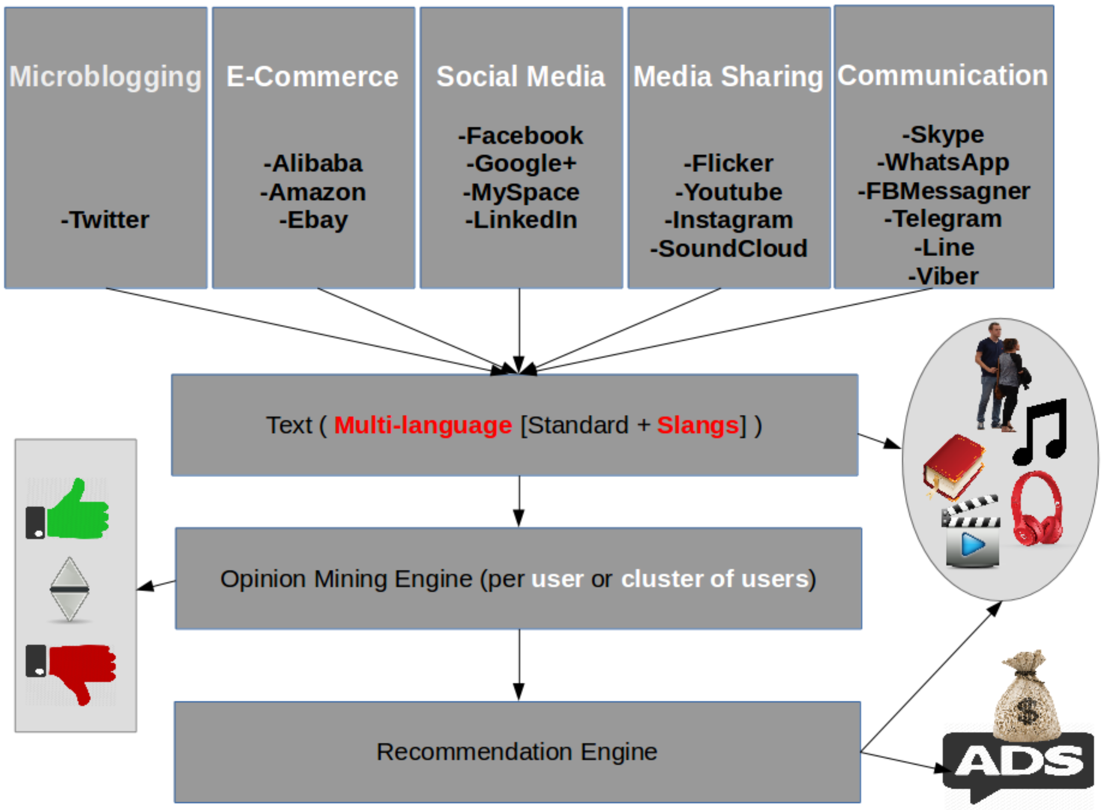


Figure 3.1: Conceptual Model

as well as the recommendation results (content or ads) and therefore maximize business revenue. However, the opinion mining process is not straightforward, especially when many languages are being supported by the digital communities. That is where a comprehensive knowledge base (also called Sentiment Lexicon) is required that includes opinion terms and phrases that refer either to positive or negative feedback.

Figure 3.1 also depicts that online digital communities support multilingual text for communication and interaction. Different research shows that usage of many languages introduces challenges and problems to sentiment analysis. For instance, there are not enough knowledge bases of different languages to feed sentiment analyzers [20]. In addition, mutlilingual textual support on online digital communities introduces unexpected problems [12]. This survey focuses on sentiment analysis in mutlilingual settings. Accordingly, this scope identifies the framework for the literature review that is used to collect, classify, analyze previous research work, and finally to identify the main challenges and also to propose

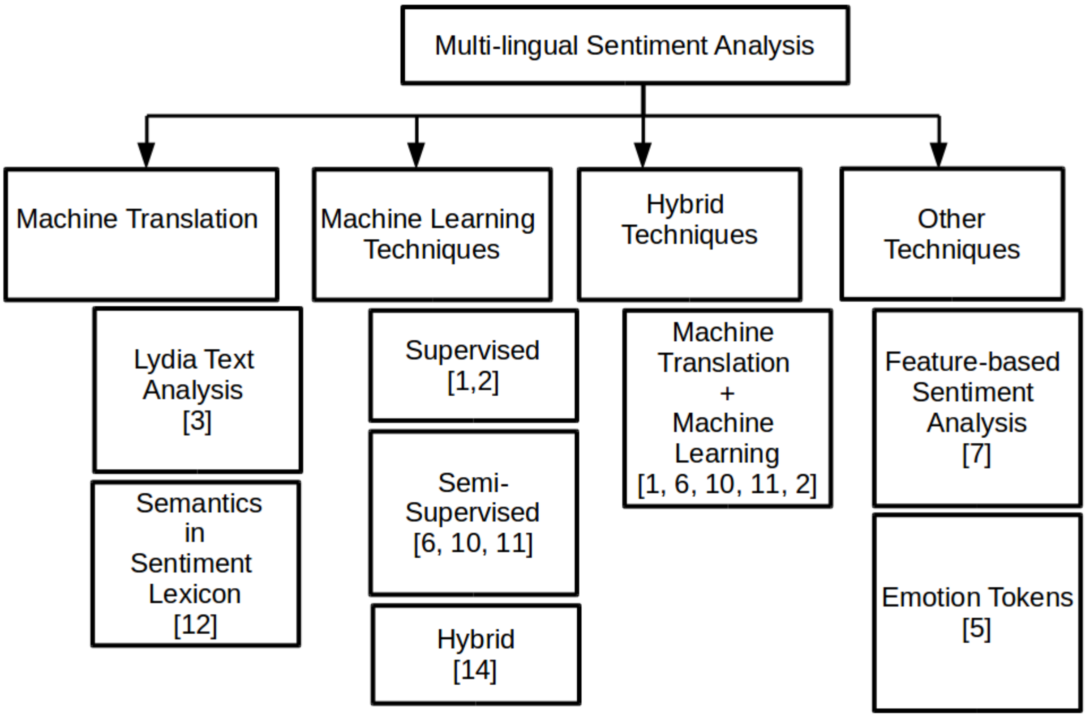


Figure 3.2: Classification of Techniques

directions for future research. Ultimately, we want to answer the following research questions:

- Do many languages introduce challenges to sentiment analyzers?
- What are the main challenges and issues of multilingual sentiment analysis?

The main contribution of this survey is to review recent literature of MLSA. First, this survey classifies different literature based on different techniques, data sets, and languages used in the research experiment. Second, this survey introduces challenges and issues in the MLSA domain. Finally, this survey gives directions for future research. Fig. 3.2 shows the classification of different techniques used in the literature for multilingual sentiment analysis.

This chapter is organized as follows: Section 2 is about slang development and how would it affect the sentiment analysis. Section 3 includes the research method and summarizes different research articles, and section 4 states the related work. In section 5, we present different techniques used to address MLSA problem. Finally discussion and conclusion are tackled in sections 6 and 7.

3.2 Slang Development and Sentiment Analysis

The Life of Slang book [6] discussed the evolution of slangs and how they are developed in different contexts. In addition, the author discussed the reasons for such slangs to be developed. The author only focused on slangs in the English-speaking world. However, some facts have been obtained from this book that could be generalized to worldwide slangs. The book concludes that Slangs are continuously developed, especially in dense social networks and communities. In addition, slangs are different depending on their context. Finally, usage of slangs might create misunderstandings between nations, as well as between generations. Although these facts have been obtained from a book that focus on English slangs only, it could be validated on other world slangs through personal or online interviews.

Another research study focused on how understanding slangs is very important for businesses. "Understanding customer's feelings, perceptions and satisfaction is a key performance indicator for running successful business. Sentiment analysis is the digital recognition of public opinions, feelings, emotions and attitudes. People express their views about products, events or services using social networking services. These reviewers excessively use Slangs and acronyms to express their views" [17].

3.3 Research Method

To review the literature and state of sentiment analysis, we followed a theoretical study method. First, we identified a scope for the study as well as a process for source selection. We looked for relevant sources in conferences/workshops proceedings as well as journals and magazines. For searching, we used online databases such as IEEE, ScienceDirect, ACM, Elsevier, Springer, and Google Scholar based on a list of identified keywords. After that, we validated the sources based on some factors such as author profile, number of citations, and ranking of conference or journal. Second, by skimming abstract, introduction, and conclusion sections, we categorized collected sources in different groups based on their scope as well as our scope. Finally, each source was reviewed and analyzed individually. Then a comparative study was conducted among different sources to provide classification of techniques, methodologies, data sets, and supported languages.

Table 1 summarizes the different articles that we collected. The third column of the table states the technique used in the article to address the issue of MLSA. We classify these techniques into different categories. First, MT refers to techniques based on machine translation. Second, ML refers to techniques based on machine learning. SS-ML refers to semi-supervised machine learning technique, S-ML refers to supervised machine learning technique, whereas H-ML means hybrid machine learning techniques.

Table 3.1: Summary of Articles

Ref.	Year	Algorithm	Domain of Data	Data Set	Languages	Tools
[2]	2012	MT + S-ML	News	New York Times Text,(2002-2005)	French, German, Spanish	TS (Bing, Google, Moses, Yahoo) Machine Learning (SVM)
[4]	2008	MT	News and blogs	Articles from online worldwide newspapers (May 1 to May 10, 2007)	Arabic, English, Chinese, French, German, Italian, Japanese, Korean, Spanish	IBM WebSphere Translation
[8]	2013	MT + SS-ML	Movies and product reviews	English and product review (Amazon website). Turkish movie review (Beyazperde,website).	English, Turkish	Machine Learning(Naive Bayes, SVM, Maximum Entropy) TS (Google)
[13]	2014	SS-ML + MT	Book reviews	Amazon reviews	English, French, German, Chinese, Japanese	TS (Google). Machine Learning (Support Vector Machine).
[19]	2013	H-ML	Movies reviews	Muchocine corpus for Spanish movies reviews.	Spanish, English	Sentiment Lexicon (SentiWordNet). Machine Learning (Rapid Miner tool)
[15]	2014	MT	Dutch reviews	Opinion-based Dutch documents (sites, forums, and blogs)	English, Dutch	SentiWordNet, WordNet, DutchWordNet
[10]	2014	MT + Feature Extraction	Twitter and Product Reviews	Tweets + Product reviews (English and Japanese websites)	English, Japanese	LDA (Latent Dirichlet Allocation)
[7]	2011	Emotion Token and Propagation Algorithm	Twitter	Tweets (Stanford SNAP)	English, German, Spanish, and Portugese	SentiWordNet, Google Translation API
[14]	2015	MT + SS-ML	Book Reviews	Amazon Book Reviews	English, Chinese, Japanese, and French	Support Vector Machine, and Google Translate Engine
[3]	2014	MT + S-ML	News	New York Times Text Corpus (2002 - 2005)	English, French, Spanish, and German	Support Vector Machine, Google Translate, Yahoo Translator, Bing Translator

3.4 Related Work

The fast growth of information sharing in online digital communities makes sentiment analysis an important task for extracting opinions from large volumes of natural language text. In the past few years, researchers made many efforts to study and review different issues and challenges related to sentiment analysis. As a result, different techniques and approaches have been reviewed. For instance, a three dimensional comparative study has been conducted to illustrate different techniques that are being used in sentiment analysis [11]. The dimensions are related to three important factors, namely sentiment lexicon, usage and training of data sets, and thirdly whether the sentiment analyzer depends on specific language or is language independent. In like manner, the authors in [5] reviewed different techniques used in sentiment analysis but only focused on the Twitter platform.

Other research has focused on studying recent literature to identify issues and challenges in sentiment analysis [12]. This study suggested a limitation in availability of survey papers in this domain. In addition, the study suggested that available research only focuses on one language: English. Moreover, the study also stated that multi-language support in online digital communities introduces many problems and challenges to the sentiment analyzer. Finally, the study suggested that using a knowledge base to feed a sentiment analyzer would ensure better results. However, building this knowledge base is challenging since a sentiment lexicon is not available in all languages [20].

Finally, some researchers focused on particular issues in sentiment analysis. For instance, one study used a chronicle-based survey to analyze different aspects of negation (as a subjective factor). The study concluded that negation has a great impact on the outcome of sentiment analysis process [24]. Subjectivity usually refers to personal opinions that are based on assumptions whereas the outcome of the sentiment analysis is often called polarity which indicates whether opinions in a given text is positive, negative, or neutral.

Related work highlighted some challenges and issues for sentiment analysis. One of these challenges in multilingual sentiment analysis. However, to our best knowledge, there are no comprehensive survey papers that focus on the issue of MLSA. Therefore, different from existing survey papers, our objective is to conduct a comprehensive literature review to study different techniques and approaches used to address the challenge of MLSA, and figure out the current limitations.

3.5 MLSA Techniques

3.5.1 Machine Translation

Machine translation is a type of computational linguistics that focuses on how a computer program translates a piece of text from one language to another (e.g., Arabic to English). Some research discusses the usage of machine translation in multilanguage settings to perform sentiment analysis. Namely, a study of international sentiment analysis for news streams [4] used a generalization of Lydia sentiment analysis to extract sentiment of daily news published in different languages. The Lydia system mainly extracts named entities (e.g., person or product) from a corpus. Then, using a sentiment lexicon of positive and negative adjectives, the polarity of specific entity (in a given sentence) is calculated. In light of this, the study uses two steps to calculate the sentiment score for an entity. First, given a document in a specific language (e.g., Arabic), IBM WebSphere Translation server translates the document to English. Second, using Lydia system, the named entities are first identified, and then the daily sentiment score for this entity is calculated. Finally, the study concluded that some languages have different sentiments from others and this issue could introduce bias to sentiment analysis. Consequently, normalization of sentiment polarity is required to allow comparison between different languages.

The same study [4] reported that machine translation is a reliable technique for multilingual sentiment analysis. However, the authors reported a limitation for using machine translation that it introduces translation errors and also affects the text formatting (e.g., sentence fragmentation). Other research studies reported that incorrect translations affect the performance of sentiment analysis [2].

Another study [15] used machine translation guided by semantics. The authors of this study proposed a novel approach to expand existing sentiment lexicon of a target language (e.g., Dutch) using semantics in a reference language (e.g., English). For instance, Dutch documents are first translated into English. Afterwards, the authors calculated the sentiment scores of translated documents. Then, the authors considered the semantics between words in the reference language (e.g., to identify synonyms). Finally, the semantics are mapped to the target language (i.e., Dutch) and accordingly fed into the sentiment lexicon of the target language. The authors highlighted that using this hybrid approach enhances the sentiment analysis compared to baseline machine translation approach. In addition, the authors concluded that the sentiments is not only depend on word meaning, but also depend on language-specific semantics.

3.5.2 Machine Learning

Machine learning is a discipline in computer science that focuses on implementing algorithms that can automatically learn from and make forecast on data. It comprises different techniques for learning the algorithm, namely supervised, unsupervised, and semi-supervised learning techniques. First, supervised learning using labeled data. This means input examples with the expected output for each example are pre-defined and used to train the algorithm. Then, the algorithm receives a new unseen input that is similar to any of the inputs used in the learning phase. Accordingly, the algorithm will be able to predict the output for that input. Second, unsupervised learning allows the algorithm to train without any labeled data. The algorithm defines the structure of the input data during the training phase. Finally, semi-supervised learning combines both the first and second models.

In MLSA literature, different studies used machine learning to train algorithms with sentiments using one or more language sentiment resources. Notably, in MLSA domain, researchers used machine learning techniques with machine translation. For instance, in [2], the authors used supervised machine learning technique for classification of sentiments. On the other hand, in [8, 13], the authors used semi-supervised learning model by using labeled and unlabeled sentiment data from different languages. Finally, a study [19] used hybrid approach by combining supervised and unsupervised learning techniques to detect sentiments in Spanish reviews. However, in the MLSA domain, linguistic resources (large amount of sentiment lexicon) for sentiments are not rich enough in many of the languages [2, 19].

3.5.3 Hybrid Techniques

Some research studies integrated two or more techniques to assess the performance of MLSA [2, 8, 13]. The majority of hybrid techniques depend on combining machine translation with machine learning approaches for cross-lingual sentiment classification (CLSC). CLSC is based on the idea of using labeled sentiment resources (positive and negative sentiments) from a specific language to classify and analyze sentiments in another language.

In [2], the authors used machine translation together with machine learning to classify sentiments for text in a given language (e.g., Spanish). The study uses a dataset of English sentences that represent opinion items (i.e., opinion holder, entity to which opinion is targeted, and opinion polarity). The authors of this study perform three steps to assess the performance of MLSA. First, they divide the data into two sets: the training set and the testing set. Second, using machine translation services such as Google, Bing, and Moses, the data is translated from

English to a different language (e.g., Spanish). Third, the study uses Support Vector Machine (SVM) as a classifier for sentiments in a given language. The translated training data set is used to train the classifier. Then, the testing data set is used to evaluate the classifier. Finally, the study concluded that machine translation as a technique is reliable to translate sentiment training data from English to other languages.

Another study [8] investigated polarity detection in cross-lingual settings using hybrid technique (machine translation and semi-supervised machine learning). However, the scope of this study is different from the first mentioned one. The authors in this study wanted to validate whether classification of sentiments in a given target language (e.g., Turkish, the language for which sentiments need to be classified) is affected by the size of training set used to learn the classifier. To achieve this, the study depends on co-training the classifier by labeled and unlabeled data from different languages. The labeled data in this case represents movies and product reviews in which each review either mapped to positive or negative feedback. Similar to [2], the data set is divided into a training data set and a testing data set. Finally, the study suggested that expanding the training set by using different languages will not necessarily enhance the performance of polarity detection and classification. This happens because of culture biases in different languages (e.g., the way people like, dislike things), and therefore this introduces dissimilarity issues when using different languages. However, the study concluded that using semi-supervised learning approach with unlabeled data improves the performance of CLSC.

Similar to [8], another study [13] showed that the usage of unlabeled data for learning classifier enhances the classification of sentiments in the target language. In this study, labeled sentiment data from different source languages are translated to the target language to build the training set for the classifier. However, the authors claimed that due to different linguistics and writing styles, some terms may not be covered during the translation process. The problem is that training and test data are from different languages which are source and target languages. Accordingly, on an iterative base for a finite number of rounds, the unlabeled data from the target language are added to the training data set to learn the classifier. The study reported that incorporating unlabeled data in the learning process enhances the performance of CLSC. Finally, the study stated two challenges. First, translation services available will not freely translate large amount of text. Second, it is challenging to choose a source language to obtain the labeled sentiment data that will be used to build the training set of the target language.

3.5.4 Other Techniques

There are some techniques that cannot be categorized as machine translation, machine learning, or hybrid approaches. Some researchers used feature based data analysis in Twitter to analyze sentiments of tweets [10]. The authors of this study extracted product's features by analyzing online reviews in two languages: English and Japanese. Then, the authors created features groups which are pairs of English and Japanese features (by machine translation and matching of synonyms). Accordingly, each feature group represents multilingual features of a specific product. Afterwards, the authors calculated the sentiments of tweets that contain these product's features. Although the authors validated their approach experimentally, there are some limitations such as usage of manual evaluation of extracted features. In addition, the number of extracted features for each product is limited and only restricted to two languages: English and Japanese. Finally, the authors assume that each tweet contain one feature at most, and the sentiment of the feature represent the sentiment of the whole tweet. However, they are ignoring some important factors such as negation.

Other researchers used emotion tokens to address the problem of MLSA [7]. The authors considered Twitter domain in this study and proposed a novel approach to build a sentiment lexicon from emotion tokens that is language-independent. First, the authors extracted different emotion tokens from multilingual tweets . Second, the authors build a graph of emotion tokens with normal words based on their co-occurance in tweets. After that, the authors used sentiment lexicon (SentiWordNet) to label the normal words with polarity score, and then propagate this score to the whole graph. Accordingly, a sentiment lexicon of emotion token is built with polarity scores that can be used to analyze the sentiment of a given tweet regardless its language. Finally, the authors suggested that the proposed approach provides better performance compared to baseline approaches of sentiment analysis in Twitter.

3.6 Discussion

In this section, we present some statistics and analysis based on different techniques and approaches considered by researchers to address the MLSA problem. First, we want to mention a limitation of this survey that we only considered a few number of articles and also the majority of them is recent (i.e., published in the past three years). However, the study shows that the trend of researchers (more than 70% of articles) is to use hybrid techniques to address MLSA.

Researchers used different datasets from different domains. However, the focus of researchers is on reviews' domain (around 60% including movies, books, and

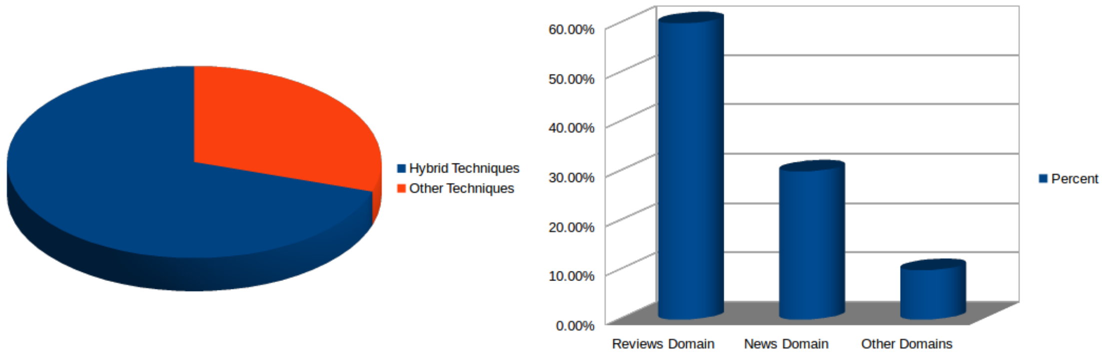


Figure 3.3: Statistics and Analysis

products), compared to news' domain (30%), and few of them considered Twitter domain. Most of the data sets is publicly available, and researchers used crawlers to get reviews and news from online websites. Fig. 3.3 shows statistics based on different techniques used in the literature for MLSA.

Machine Translation is very important and almost used by all researchers either solely or combined with other techniques such as machine learning, or feature based techniques. However, different researchers stated some limitations of machine translation technique. First, wrong translation sometimes lead to problems with sentiment analysis [2]. Second, writing styles and sentiments' words are different among languages [13]. The same study also highlighted that online services that provide machine translation have a limit, and therefore it would be expensive to translate a large corpus. Finally, machine translation suffers from fragmentation problem. That means the sentence might lose its structure after the translation process [15].

The literature highlighted some limitations with currently available sentiment lexicons. For instance, most of researchers used English as a reference language as a sentiment lexicon[13, 14]. That means researchers first translate available data to English, and then use sentiment lexicon in English for the analysis. As a result, we can conclude that sentiment lexicons are not rich in most of the languages, the issue that has been reported by some studies [2, 14, 19].

Other researchers suggested that sentiment lexicons have some problems with domain-specific corpus [20]. Accordingly, we can conclude that sentiments lexicons are not rich enough and also they are not context-oriented. Finally, some researchers highlighted that there are biases among sentiments of different languages [4, 8]. The authors suggested that the culture differences is the main reason that introduces these biases.

The study shows that researchers validated different approaches experimentally considering specific languages. However, the focus of authors was on specific set of languages. For instance, the majority of studies (more than 50%) have used English, French, German, and Spanish. This indicates that the authors ignored important widely used languages such as: Arabic, Portuguese, and Russian. Finally, a list of core observations that have been conducted from the literature could be listed as follows:

- Sentiment lexicons are not rich in all languages.
- English is mostly used as reference language for sentiment lexicon (knowledge base).
- People use slangs to communicate online, and this would introduce challenges for businesses to analyze people's opinion and feedback about different entities (e.g., photos, movies, products, books). Especially that sentiment lexicons available have some limitations in different languages as highlighted by the literature review.
- There are sentiment biases between different cultures and languages. That's because people use different writing styles to express their feelings.

3.7 Conclusion

This survey presented the state of the art techniques used to address the problem of MLSA. The study categorized and summarized the reviewed articles based on different factors. The main contribution of this survey is that it analyzes and presents different techniques used for MLSA. In addition, the study also identifies the limitations and challenges of sentiment analysis in multi-language settings.

Notably, most of the researchers used hybrid techniques to address MLSA problem in different domains. However, the main focus was on product reviews' domain. The study shows that regardless the efforts of different researchers in MLSA domain, there are still some limitations and open research issues. First, there are still no enough sentiment resources in different languages compared to English. Future research should propose novel approaches to build rich sentiment lexicons in different languages. Second, machine translation suffers from some problems, especially culture biases and fragmentation. Third, most of the experiments of MLSA were conducted in products' reviews domain. However, future research should focus on other domains such as Twitter, Facebook, blogs, and other social platforms where users share sentiments about different entities. Finally, the literature used English as a reference language for a sentiment lexicon. However, future research might consider and compare different languages as a reference to a sentiment lexicon. In addition, future research should consider different widely used languages to validate their approaches such as: Arabic, Russian, and Portuguese.

Based on the literature review, the proposed solution in this thesis will consider the identified limitations of sentiment analysis in multilingual settings. In light of that, the proposed solution will provide an innovative approach to build a rich knowledge base of sentiments (words/idioms) used in different languages, including the context where these sentiments are being used.

Chapter 4

The Proposed Solution

In Chapter 2, we presented and analyzed the observations and problems we concluded from the personal interviews, as well as from the online survey. In Chapter 3, we presented and analyzed the observations and problems we concluded from the literature review about sentiment analysis in multi-languages settings. When we designed our proposed solution, we considered all these observations and problems. This chapter is organized as follows: Section 1 presents the initial scope of our solution. Section 2 discusses the main features of Slangsh and the design decisions. Section 3 explains crowdsourcing and different incentives that have been used to encourage people to use Slangsh. Finally, section 4 explains why a simpler solution would not suffice to achieve the required goals.

4.1 Scope

Initially, our proposed solution (Slangsh) will be available as an Android application with three different display languages (i.e., for display) which are: Arabic, English, and Spanish. Accordingly, the main focus of the first version of our solution is on Arabic, English, and Spanish slangs. The reason is that we want to focus on testing our solution on few languages at first. Then based on the evaluation, we could improve the solution and scale up to include more languages. However, during the beta testing and evaluation stage, we might allow users from different countries to try the solution, so we might get some slangs in different languages as well.

4.2 Features and Design Decisions

The proposed solution is based on crowdsourcing and collaborative learning. This means that people (users) who are going to use the solution can have different roles. For instance, one user might share his native slang, while another user is browsing and learning slangs posted by others. More about crowdsourcing and incentives for people to use our solution (currently, the Android app) is in section 4.3. We decided to develop our proposed solution as an Android application, so that we can test and validate it with real users. The main features developed in the app, as well as some decision decisions are presented in the following subsections.

4.2.1 Slang Demographics

From the interviews and the online survey (presented in Chapter 2), there was some important observations about slang demographics:

- There are slangs in each language and country.
- Slangs are different for each age generation.
- Slangs in specific country are different over cities.
- People might not understand slang from other country, even if this country speaks the same native language as they speak (e.g., people from Spain and Mexico both speak Spanish).

We considered these observations in our proposed solution. Upon registering on the app, we ask the user to choose his native language, home country, and home city. If the user wants to add a new slang, native language and home country will be attached automatically based on registration's data. However, the user will need to choose the city of the slang if this slang is being used exclusively in specific city in his country. In addition, the user will choose age range for the slang. Fig. 4.1 shows how the user can choose the slang demographics using the Android app.

4.2.2 Slang Definition with Translations

In our proposed solution, we ask the user to provide at least one definition in specific language and optionally a translation for this definition in another language. Fig. 4.2 shows how the user can add a definition to a new slang using the Android app. As the proposed solution is based on collaborative learning and crowdsourcing, any user can add a translation for the slang definition while browsing the slangs. For instance, if a user is browsing an English slang that has an English definition, and this user can speak both English as well as Spanish, the user can add a new translation in Spanish for the slang definition. Fig. 4.3 shows that the user has the option to add a new translation using the app.

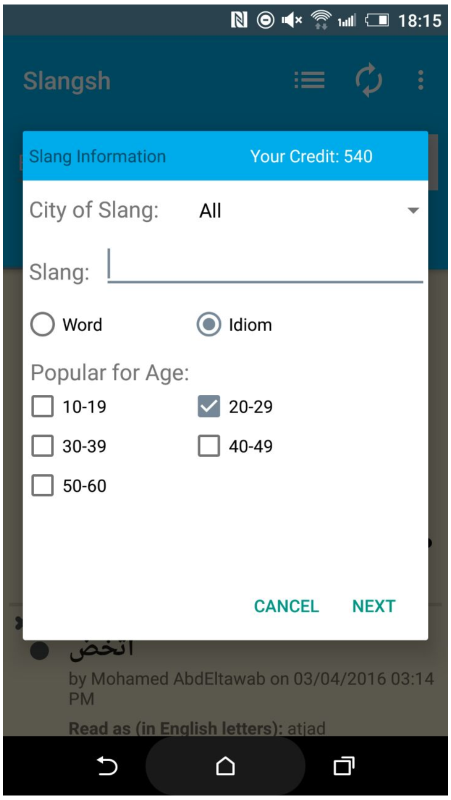


Figure 4.1: Slang Demographics

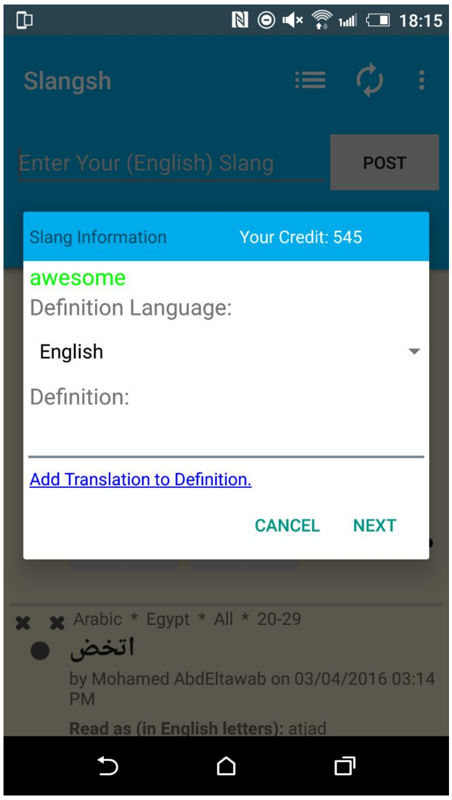


Figure 4.2: Slang Definition

4.2.3 Sentiments

There are two important observations obtained from the interviews and the online survey (in Chapter 2), as well as from the literature review (in Chapter 3). These observations are as follows:

- People use slangs in daily life communications, as well as for online communications (e.g., texting on social media).
- "People express their views about products, events or services using social networking services. These reviewers excessively use Slangs and acronyms to express their views" [17].

In our proposed solution, we introduced a feature that considers these observations that is to attach different sentiments with each slang. In order to achieve that, when the user shares a new slang, he must select at least one sentiment for this slang. However, if the slang has not attached sentiments by nature, the user should just choose "Neutral" from the sentiments' list. Currently, we focus on

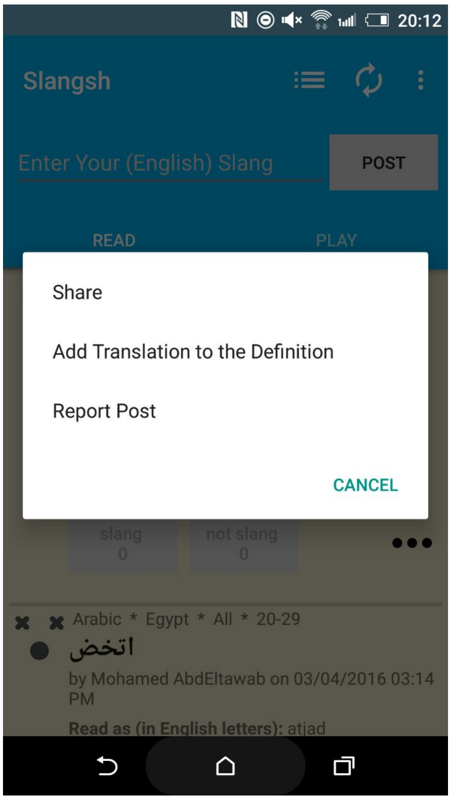


Figure 4.3: Add New Translation

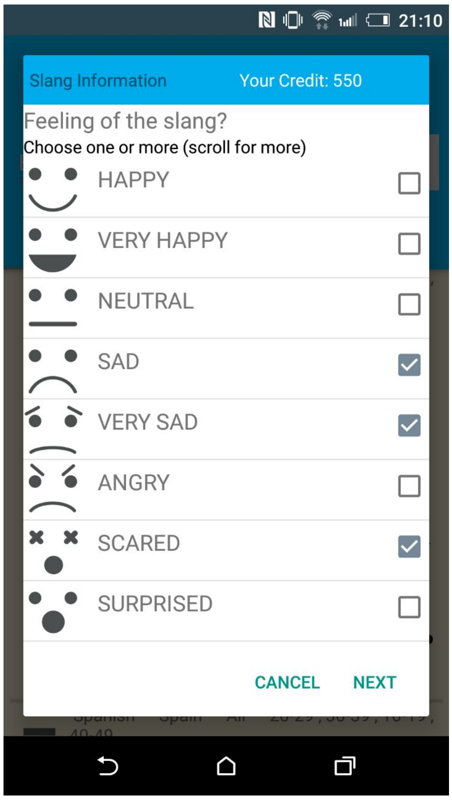


Figure 4.4: Attach Sentiments

15 different sentiments only which are: positive, negative, happy, very happy, sad, very sad, angry, disgusting, accepting, rejecting, interesting, scared, surprised, fun, and neutral. Fig. 4.4 shows how the user can attach sentiments to a slang using the app.

4.2.4 Contexts

From the literature review about sentiment analysis (in Chapter 3), we have concluded two important observations regarding slangs, sentiments lexicons, and context information (e.g., street, social, school). These observations are as follows:

- Slangs are being developed in different contexts [6].
- Available sentiment lexicons used for sentiment analysis and opinion mining are not rich enough in all languages and also they are not context-specific [20].

It was important to consider these observations in our proposed solution. Accordingly, in the Android app, we allow the user to label each slang with at least one context. Currently, we are testing only 10 contexts which are: social, street, family, abbreviation, technology, politics, school, internet, sport, and business. Fig. 4.5 shows how the user can attach contexts to a slang using the app.

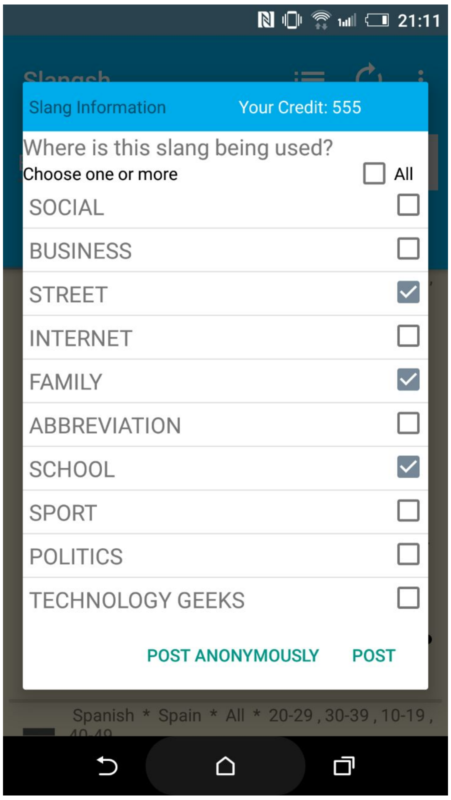


Figure 4.5: Attach Context

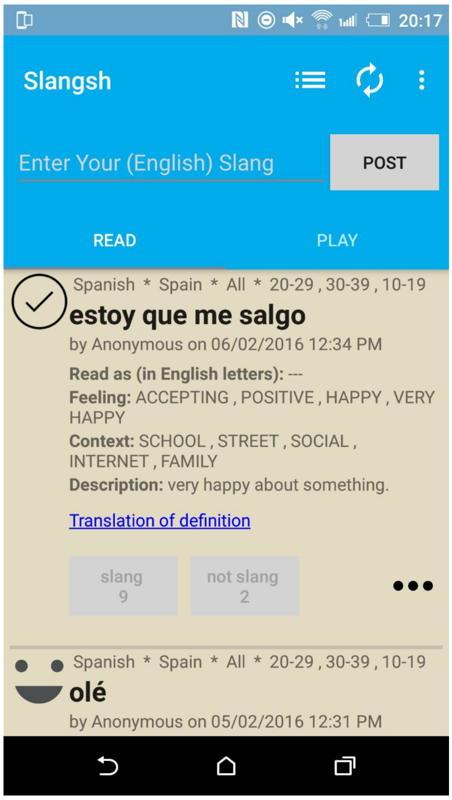


Figure 4.6: Slang Feed

4.2.5 Browse and Filter Slangs

In the previous subsections, we discussed features to add a new slang using the Android app. We also mentioned that our solution is based on crowdsourcing, so while some people are sharing their native slangs, other users might be interested to just browse slangs. Therefore, this subsection is about browsing and filtering slangs. When the user firstly open the app, he will be able to browse slangs in different languages by scrolling in the "Read" tab. Fig. 4.6 shows a sample of slangs' feed while scrolling in the "Read" tab. However, users want to browse slangs in specific language. Since, we currently focus only on three languages:

Arabic, English, and Spanish, the user can use the app to filter the slang feed and browse a specific language. Fig. 4.7 shows that the user is able to filter the slang feed to browse Arabic, English, or Spanish slangs.

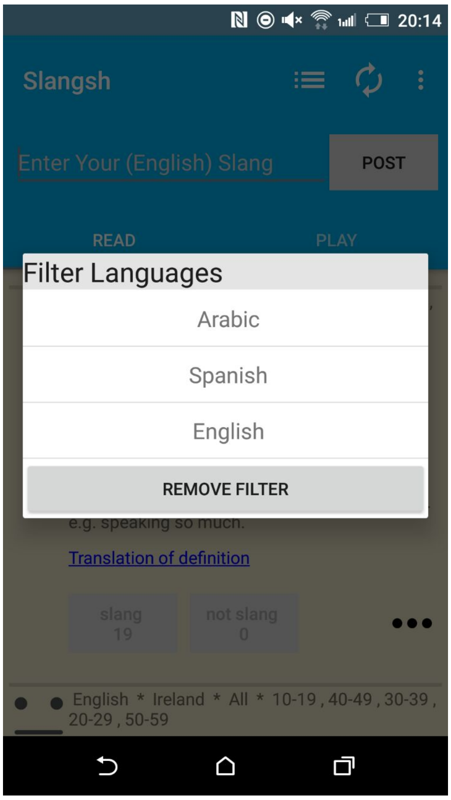


Figure 4.7: Filter Slang Feed

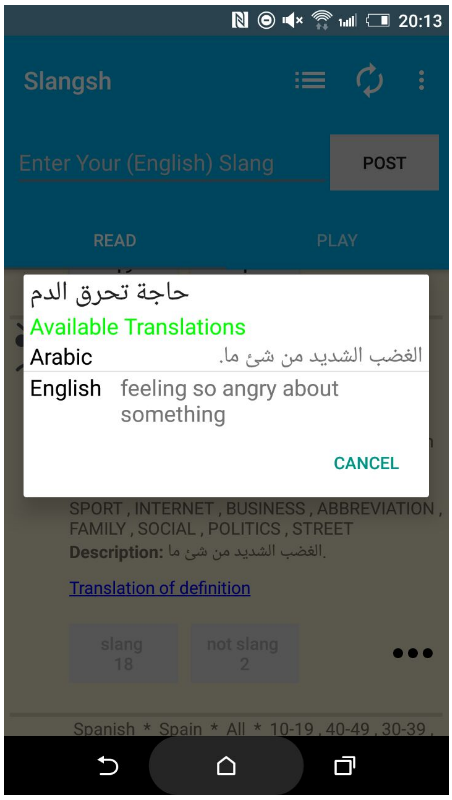


Figure 4.8: Slang Definitions

As shown in Fig. 4.6, there are some information for each slang in the feed. First, there is some information about slang demographics that includes: Language, Country, City, and Age (e.g., Spanish * Spain * All * 20-29). Second, the text of the slang either it is a slang word or idiom. Third, there is some information about the author of the slang (i.e., the user who posted the slang), as well as the slang's creation date. To consider the privacy concern, we allow the user to post either by his identity (i.e., user name), or as an anonymous. This is shown in Fig. 4.5. Forth, only for non-English slangs, a text that allow the user to read the slang in English letters. We call this feature "Franko", and we currently using it because there is no feature to record the slang. However, we want to allow everyone who knows English to be able to read any slang in different languages. Franko means that a user writes his slang, but using the English alphabet. This means that he will choose the letters in English that are similar to the pronunciation of the letters in his native language. The purpose is that people who do not know about specific slang language, but know English, can still read and pronounce this slang by reading it in the franko format. For instance, a Spanish slang (te cantan los sobacos) will be in Franko (ta kantan los sobakos). The accuracy of this feature is not guaranteed, and we are going to validate it during the evaluation phase. Fifth, the sentiments list attached to this slang. We chose the first sentiment as a sample feeling for this slang. You can notice that in Fig. 4.6 from the icon shown in the left upper corner which represent one of the slang's sentiments. Sixth, this is the list of contexts where this slang is being mostly used as identified by the author of the slang. Seventh, this is the definition of the slang in specific language as identified by the author. As we mentioned in the previous subsections, the user can add a translation for the slang's definition while posting it, or other users might add a translation later while browsing the slang feed. Therefore, there is a link under the slang slang definition that allow the user to check if there is available translation for the definition in other languages than the main definition. Fig. 4.8 shows an example for slang that has definition translated in more than one language.

Finally, there are three buttons to vote for the slang either to approve that it is slang or not a slang, and also enable you to report the slang (in Fig. 4.3). These voting and reporting features are used for quality assurance, as we want to be sure that people are actually using the solution to add only slang words or idioms, but not standard or basic words or idioms. In Fig. 4.6, it is shown that these buttons are disabled, and that's because the logged in user in this case does not speak the native language of the slang (in this case Spanish slang, and the user's native language is English). We thought that it would be better to only enable people who speaks the same native language of the slang to vote for slang. However, anyone can report a slang.

4.3 Crowdsourcing and Incentives

There are many available definitions on the internet for "crowdsourcing". However, we would like to define it as the process that utilizes the power of the crowds (i.e., people), so that they are responsible for doing some online activities while they are receiving some incentives in return. These activities include knowledge sharing and content generation. This means that we are going to outsource specific tasks to be performed by people. Accordingly, the main activities that people are going to do on our proposed solution is to share their native slangs, add translations to slang's definitions, ensure the quality of slangs by voting or reporting them, and finally share the content over different social media channels. Therefore, people (i.e., users of the proposed solution) will be responsible for generating the content.

The incentives that these users will get in return could be intrinsic or extrinsic incentives as explained in the following subsections.

This model of crowdsourcing has already been employed by companies in different application areas [23] such as computing (e.g., web or mobile apps), and marketing. For instance, Quora[1] is a very popular question answering service that has been launched in June, 2009. Quora is based on crowdsourcing where users are responsible for generating the content either by asking questions or providing answers to already existing questions. On the other hand, Wikipedia[2] is a very famous website that is based on crowdsourcing that allow people to collaboratively share information and knowledge.

4.3.1 Intrinsic Motivation

"Intrinsic motivation is defined as the doing of an activity for its inherent satisfactions rather than for some separable consequence. When intrinsically motivated a person is moved to act for the fun or challenge entailed rather than because of external prods, pressures, or rewards"[22]. Based on this definition, it is clear that this type of motivation is usually driven from inside a person, and some examples for such motivations are: passion, self-interest, fun and self-satisfaction. Therefore, individuals who are driven by intrinsic motivation usually waiting no rewards in return for their actions or contributions. For us, it is very important that the majority of people who are going to use the solution will be driven by some intrinsic motivations. Accordingly, they are going to be motivated to share their native slangs with others. In our proposed solution, the intrinsic motivation factors could be summarized as: the sense of belonging to a community and enjoyment of using the solution.

First, the sense of belonging and contribution to a community. If individuals have this motivation, they will be encouraged to share their native slangs with other people. Second, enjoyment and having fun while using the app. In this case individuals are enjoying their time using the app and having fun by sharing their native slangs. To ensure that people are going to enjoy their time, currently the proposed solution (the Android app) contains a tab called "Play". From this tab, users can try to guess slangs in different languages based on given contextual information. In addition, they are able to dare their friends on different social media channels to guess specific slang. Fig. 4.9 shows an example to browse slangs in the "Play" tab. The information available is the same as the information of slang in the "Read" tab (discussed in Subsection 4.2.5), except that the slang word or idiom is replaced by another text. This text provides an information

[1] https://www.quora.com/
[2] https://www.wikipedia.org/

about the number of characters that the slang word or idiom has. Then the user should try to guess this slang word/idiom based on this information and all other information attached with the slang. Fig. 4.10 shows that the user can challenge his friends by sharing a slang, so that they can guess this slang based on the available information.

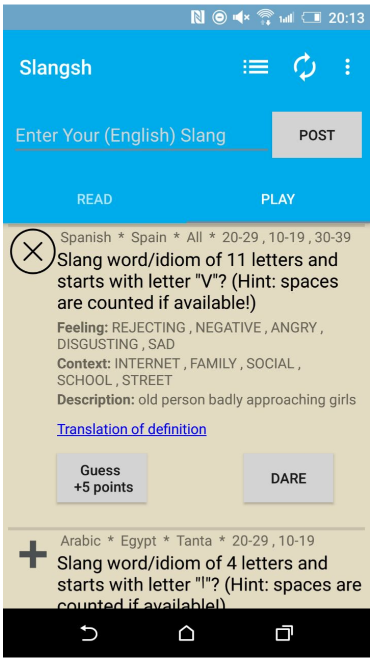


Figure 4.9: Play Feed

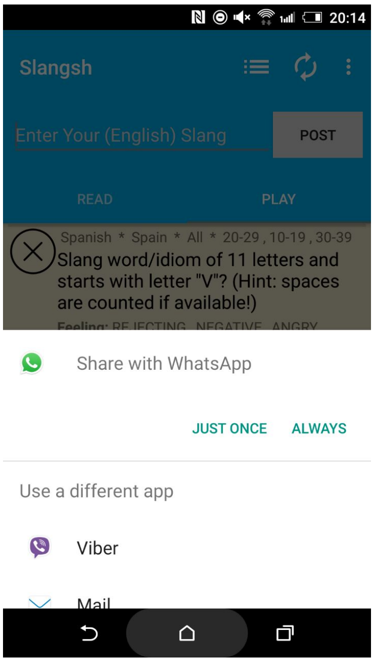


Figure 4.10: Dare Friends

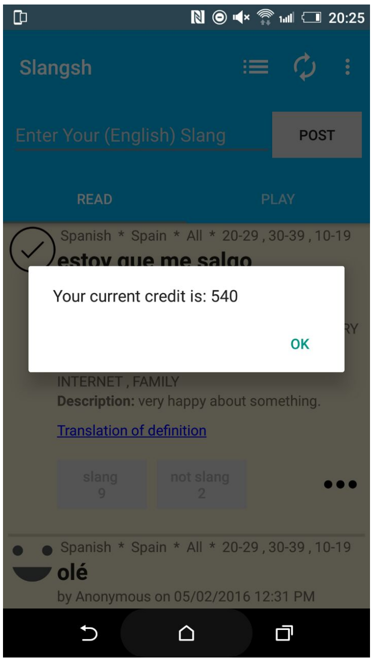


Figure 4.11: Check Credit

4.3.2 Extrinsic Motivation

"Extrinsic motivation is a construct that pertains whenever an activity is done in order to attain some separable outcome" [22]. For this type of incentives, people are encouraged to do an action while they are expecting to get something in return such as an award or any other outcome. In our proposed solution, we have two extrinsic motivational factors: karma and learning slangs in different languages. First, user karma could be based on activity karma (e.g., sharing slang or adding a new translation), or quality karma (e.g., sharing bad content that has been reported by other users). Currently, we only consider and implement the activity karma in the proposed solution. Whenever a user shares a new slang or add a new translation for a definition, she gets some extra credits. Currently, the user can only check her own credit. However, in the future, this credit will be attached to a specific title (e.g., Slang Master), as well as could be compared with other users. This will encourage competition between users and motivate them to build reputation by improving their credits. Fig. 4.11 shows that the user can check her own credit on the app. The second extrinsic motivation is learning slangs from different languages using the app. These slangs are shared by other users. Accordingly, learning is considered a separate outcome from using the app.

4.4 Alternative Solutions

There might be different solutions that could be proposed to build a dictionary of slang words/idioms in different languages and countries. For instance, a wiki of slangs could be developed, where everyone can add, edit, and remove different slang information. In addition, everyone would be able to collaborate with other people to edit the slang content; however, such simple solutions would not suffice to achieve our main objective with Slangsh. The reason is that in Slangsh we consider many features and design decisions such as slang demographics, definitions and translations of slang in different languages, sentiments of the slangs, and contexts of the slangs. In addition, we consider different incentives for crowdsourcing that would motivate them to share their native slangs, and we include some features to ensure the quality of slangs shared in different languages; moreover, we care about building a structure dictionary of worldwide slangs, not only to collect unstructured data about these slangs. This shows that there is a need for a robust and comprehensive solution and that a simple solution might not suffice to build a comprehensive dictionary of worldwide slang labelled with different information and that indicates high accuracy of content.

Chapter 5

Implementation Environment

In the previous chapter, we discussed our proposed solution. We also mentioned that we decided to test this solution by implementing it as an application for Android smartphones. In order to achieve that, we have used different technologies and frameworks. The following sections in this chapter explain these technologies and frameworks in detail, and how we used them to implement our proposed solution. Fig. 5.1 shows an overview and abstraction of the architecture of the proposed solution. As shown in the figure, there are four main components. First, the front-end (i.e., the Android app that is being used by users to share and browse slangs). Second, the back-end API (i.e., the service that stores, retrieves, and processes the data). Third, the database that is being used for data storage. Finally, the cloud environment used for API deployment and for hosting the database. This chapter is organized as follows: Section 1 is about programming languages. Section 2 is about some internet technologies, and section 3 states different types of database engines we have used for data storage. Section 4 is about tools and frameworks that we have used during the implementation phase. Finally, section 5 discusses how we deployed our solution using Amazon Web Services[1] and Google Play[2].

5.1 Programming Languages

In order to develop our proposed solution, we used Java programming language for both the front-end and the back-end development. First, for front-end, we used java for Android development. Second, for back-end API, we used Java 2 Platform, Enterprise Edition (J2EE), for development. All android applications (i.e., run on Android smartphones) are being written in Java programming language [9].

[1] http://aws.amazon.com/
[2] http://play.google.com/

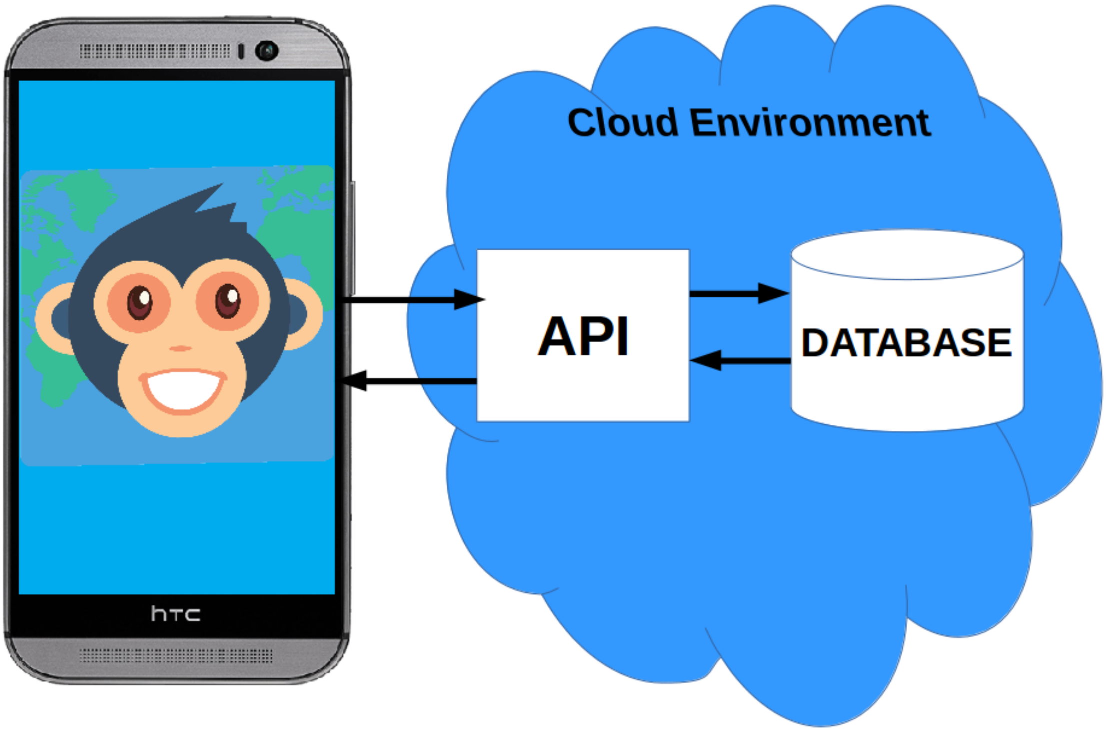


Figure 5.1: Architecture of the Proposed Solution

On the other hand, J2EE provides different components to design and develop applications on the web [16]. This is what we want in our case, since the back-end service responsible for storing, retrieving, and processing the data will be deployed on the internet. Accordingly, it could be accessed from different users from different locations.

5.2 Internet Technologies

We have used some internet technologies to develop our solution. Mainly, we used two internet standards: RESTFul web services for back-end development and JSON (JavaScript Object Notation) for data transfer between the android application and the back-end service. First, JSON[3] is a lightweight data format that is a platform independent and could be exchanged between different applications hosted on different environments. The main advantage of JSON is that it is readable and easy to be parsed and processed. In order to process the data

[3] http://www.json.org/

in JSON format on both the front-end application as well as the back-end application, we used a library called GSON[4] developed by Google[5]. This library has an implementation in Java programming language which is the language we are using in developing our solution. Second, RESTFul web services where REST is stands to "Representational State Transfer". REST describes an architectural style that identifies someone design principles and constraints should be followed to ensure that the web service will provide good performance and be scaled up and maintained easily [21].

5.3 Data Storage

In our proposed solution, we need to store people's (i.e., users of the Android app) demographic and contextual data such as native language, home country, home city, languages they speak, and languages they are interested in. In addition, we need to store data about slangs in different languages and countries (this slangs are being shared by the users). The data structure for slangs has been presented in section 4.2.5. In order to store this data, we use different storage engines: SQLite[6] and MySQL[7]. The first is a lightweight database that could be used on smartphones client applications (in our case, it is used with the Android app). The later is a very mature relational database management system that could be used with back-end services (in our case, it is used with the back-end API).

5.4 Tools

We have used a set of different tools for the implementation of the proposed solution. These tools could be summarized as follows:

- Android Studio[8]: This tool provides an integrated environment to develop, test and deploy Android applications for smartphones and tablets.
- MySql Workbench[9]: This tools provides some utilities and interface for creating, storing, processing, and viewing MySql databases.

[4]https://github.com/google/gson
[5]https://www.google.com
[6]http://sqlite.org/
[7]https://www.mysql.com/
[8]developer.android.com/tools/studio/index.htm
[9]http://mysqlworkbench.org/

- Sqlite Manager[10]: This tools provides some utilities and interface for creating, storing, processing, and viewing Sqlite databases.
- Eclipse[11]: This tool provides an integrated environment to develop, test and deploy enterprise applications for the web, written with Java programming language.
- Postman[12]: This tools provides an interface for testing the back-end API.

5.5 Deployment

After developing our proposed solution as an Android application, it was necessary to release it on the internet, so that people can download and use to share and learn slangs in different languages and countries. In order to release the Android application on the internet, we used two different services as shown in the following subsections.

5.5.1 Amazon Web Services

"Amazon Web Services is a collection of remote computing services that together make up a cloud computing platform, offered over internet by amazon.com." [1]. Mainly, we used two services from Amazon Web Services which are: EC2 and RDS. "Amazon Elastic Compute Cloud (EC2) is one of the services provided by Amazon Web Services and provides access to server instances on demand as a service. EC2 is a core part of AWS providing the compute facility for organizations." [1]. This means that EC2 provides virtual server instances that we used to host our back-end service (API). "Amazon Relational Database Service (RDS) is a fully-managed SQL database service. Amazon RDS offers an array of database engine choices to help with database management tasks such as migration, backup, recovery and patching. According to Amazon's RDS pages, Amazon Relational Database Service is a web service that makes it easy to set up, operate, and scale a relational database in the cloud. It provides cost-efficient and resizable capacity while managing time-consuming database administration tasks. Amazon RDS provides access to MySQL, Oracle or Microsoft SQL Server database engines. This means that code, applications, and tools already in use with existing databases can be used with Amazon RDS. Amazon RDS automatically patches the database software and backs up your database, storing the backups for a user-defined retention period and enabling point-in-time recovery. Compute resources or storage

[10] http://www.sqlabs.com/sqlitemanager.php
[11] https://eclipse.org/
[12] https://www.getpostman.com/

capacity associated with a Database Instance (DB Instance) can be scaled via a single API call." [1]. We preferred to choose managed database service for hosting our database at the beginning to avoid maintenance overhead.

5.5.2 Google Play Store

Google Play Store[13] is an online store owned by Google[14] that is hosting different products such as Android apps, games, music, movies, TV, books, and magazines. We used Google Play Store to deploy our Android app, so that people from different countries can download and use it. Our app name on Google Play is called Slangsh[15].

[13] http://play.google.com/
[14] https://www.google.com
[15] https://play.google.com/store/apps/details?id=com.slangsh.slangshapp

Chapter 6

Evaluation of Slangsh

After finishing the implementation, we performed some important activities before releasing the Android application publicly on the internet. These activities are pre-population of initial slang data as well as testing the functionality of the app. This chapter is organized as follows: Section 1 states the main goals of the evaluation. Section 2 explains the methodology we followed to assess our solution, section 3 describes the pre-population of initial slangs from different languages. Section 4 illustrates how we ensured that the beta testing is working as designed, and section 5 presents a comprehensive analysis of different aspects after publicly releasing the Android application. Finally, section 6 discusses current challenges and future work.

6.1 Goals of the Evaluation

Tha main goal of evaluating the proposed solution is to get useful insights and collect some statistics about different features and decision design decision we considered while developing the solution. In addition, we want to validate the solution against real user experience (e.g., by tracking user activity and behaviour), so that we could conclude what users like the most and what they do not like; moreover, we want to validate if Slangsh would improve the translation of slangs compared to current available online translation services (e.g., Google Translate). Finally, we would like to identify the current limitations and challenges in Slangsh, so that we can consider these limitations in the future and improve the solution accordingly.

6.2 Methodology

The main approach we followed to assess our solution was based on tracking users' behaviour against the proposed features and design decisions in our solution. During the implementation of our proposed solution, Slangsh, we have integrated some plugins that could help us evaluate this solution by tracking users' activity and behaviour while using the Android app. Mainly, we used Google Analytics[1] which is a platform offered by Google[2] for developers to allow them monitor and track different activities, actions, and demographic data about users who are using specific application (e.g., Web, iOS, or Android apps). In addition, we also used different automatically generated statistics from Google Play Store[3] on which our Android app is available for download by users from different countries. These statistical information about users' actions is very useful for us as they provide useful insights about what users like and do the most. In addition, these statistics provide useful implications about current challenges and issues in the solution that we should face and improve in the future.

6.3 Pre-population of Data

The first step after being done with the implementation of our proposed solution (i.e., the Android app) was to add some initial slang data. The main purpose for this decision is that we wanted people to find some initial content when they download and use the app for the first time. Accordingly, this would encourage the users to spend some time discovering different features in the app, as well as motivate them to share their native slangs.

As we are focusing currently on three languages: Arabic, English, and Spanish, we decided that the initial slang data will be from these languages. We know Arabic (Egypt), and English, so we added Arabic and English slangs manually. First, we added Egyptian/Arabic slangs based on our knowledge as it is the native language of one of the authors of this thesis. Second, we browsed the internet for the English slangs, especially we focused on the English slangs from Ireland and United Kingdom. Finally, for the Spanish slangs, we hired a Spanish girl from Valencia to input some slangs they use in their country. Accordingly, we ended up having 55 native slangs in 3 languages: Arabic (20), English(15), and Spanish(20).

[1]http://analytics.google.com/
[2]http://google.com/
[3]http://play.google.com/

6.4 Beta Testing

On 9th of March, 2016, we deployed the beta version of the Android app. As discussed on Chapter 5, we have different components (i.e., softwares) hosted on different environment. First, the Android app is on Google Play. Second, the back-end service (API) as well as the database are hosted on a cloud environment (Amazon Web Services). In order to be sure that everything is working as being designed after deployment, we enabled the application only for a closed beta testing group. In this case, we invited people we already know to try and test the app. Eventually, we ended up with few users who actually tested the app. These users were from different countries such as Egypt, Portugal, Germany, Colombia, Mexico, Italy, and Netherlands.

6.5 Releasing - Analysis of Data

For a couple of days, we validated the Android app with the beta testing group and found that it is working properly . Then, on 11th of March, 2016, we released the app publicly on Google Play, so that anyone can download and use it. We decided to wait for 3-4 weeks before starting to analyze or evaluate our solution, so that we could get some useful data for the analysis and the evaluation. The following subsections describe and analyze the collected data in details.

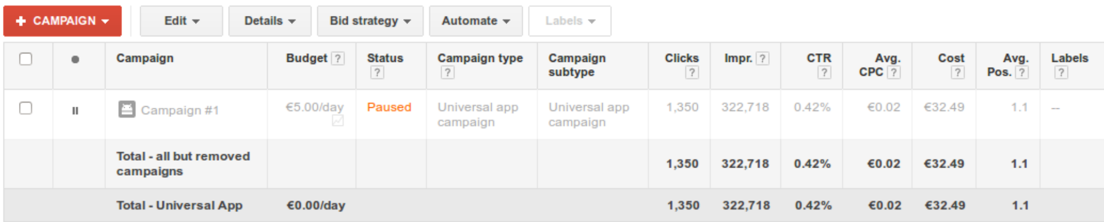
6.5.1 Promotion of the App

In order to promote Slangsh and let people know about the Android app, we used different channels of communication. At the first day and after two hours of publishing the app, we got some help from a public figure in Egypt and his name is Ahmed Rafaat[4]. He shared a link to the app on his Facebook page, and this action was led by around 100 installs and many of the users shared their native slang. Additionally, on 25th of March, we have had a live interview[5] with a famous channel in the national Egyptian tv, called ONTV[6]. Accordingly, this interview was led by around 200 downloads and shares of Arab, Egyptian, native slangs. We also created different social medial accounts that so people could follow Slangsh and learn slangs, even if they do not have Android smartphones. Consequently, we have around 800 followers (from different countries) on Facebook, Twitter[7],

[4]https://www.facebook.com/Moze3alshar3/
[5]https://www.youtube.com/watch?v=pC5d5u8TbjY
[6]http://www.ontv-live.com/
[7]http://twitter.com/

and Instagram[8]. Finally, we also ran some campaigns on different social media channels such as Facebook[9] and Google Adwords[10]. Fig. 6.1 shows a summary of the Facebook campaign. Fig. 6.2 shows a summary of the Google Adwords campaign.

Figure 6.1: Summary of Facebook Campaign



	●	Campaign	Budget	Status	Campaign type	Campaign subtype	Clicks	Impr.	CTR	Avg. CPC	Cost	Avg. Pos.	Labels
	II	Campaign #1	€5.00/day	Paused	Universal app campaign	Universal app campaign	1,350	322,718	0.42%	€0.02	€32.49	1.1	--
		Total - all but removed campaigns					1,350	322,718	0.42%	€0.02	€32.49	1.1	
		Total - Universal App	€0.00/day				1,350	322,718	0.42%	€0.02	€32.49	1.1	

Figure 6.2: Summary of Google Adwords Campaign

6.5.2 Demographic and Context Information

Using statistics from Google Analytics and Google Play Store, we are going to present and analyze some demographic and context-related data during the time (March 9th to April 8th). Users from 37 different countries have already used our Android app. Fig. 6.3 shows the top 10 countries from which users have downloaded and used Slangsh app. In addition, the figure states some statistics about user activity. These statistics will be discussed in more details in Section

[8]http://instagram.com/
[9]http://facebook.com/
[10]http://adwords.google.com/

6.5.4. As shown in the figure, Egypt is ranked number 1 for app downloads and usage. This makes sense based on the information we discussed previously in Section 6.5.1 about app promotion. In addition, Finland is ranked number 2, and this also makes sense as most of the testing and experiments took place in Finland. Finally, more demographic information about the full list of countries and the top cities from which Slangsh is being used could be found in Appendix D.

Country	Sessions	Screen Views	Screens / Session	Avg. Session Duration
	1,279 % of Total: 100.00% (1,279)	2,812 % of Total: 100.00% (2,812)	2.20 Avg for View: 2.20 (0.00%)	00:06:59 Avg for View: 00:06:59 (0.00%)
1. Egypt	674 (52.70%)	1,257 (44.70%)	1.86	00:04:02
2. Finland	373 (29.16%)	1,163 (41.36%)	3.12	00:14:49
3. Saudi Arabia	44 (3.44%)	79 (2.81%)	1.80	00:03:56
4. United States	27 (2.11%)	49 (1.74%)	1.81	00:02:36
5. United Arab Emirates	18 (1.41%)	33 (1.17%)	1.83	00:01:52
6. Iraq	12 (0.94%)	21 (0.75%)	1.75	00:02:39
7. Kuwait	11 (0.86%)	19 (0.68%)	1.73	00:05:01
8. Germany	10 (0.78%)	22 (0.78%)	2.20	00:02:55
9. Portugal	10 (0.78%)	15 (0.53%)	1.50	00:04:04
10. France	9 (0.70%)	20 (0.71%)	2.22	00:02:32

Show rows: 10 Go to: 1 1 - 10 of 37

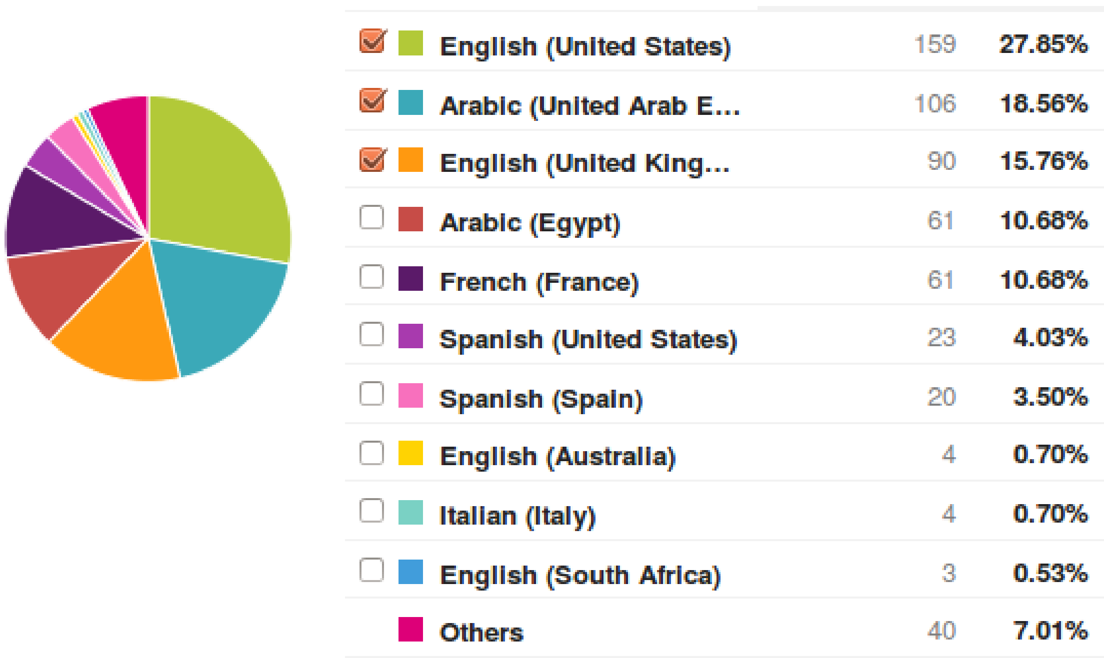
This report was generated on 4/8/16 at 5:05:06 PM - Refresh Report

Figure 6.3: App Downloads and Usage - Top 10 Countries

According to the statistics, users are using the app with 27 different display languages. With display language, we mean the default language that they are using on their smartphones. Fig. 6.4 shows the top 10 display languages currently being used by the users. As expected, English, Arabic, and Spanish are the most used languages for display as we focused more on these languages while promoting for the app. Finally, more statistics about top mobile devices on which Slangsh is being installed could be found in Appendix D.

6.5.3 User Acquisition

In almost 4 weeks, we have 571 installs (i.e., downloads) for Slangsh. Fig. 6.5 shows app installs over time. These installs for the app were by people from different countries. Fig. 6.6 shows the distribution of users who installed the app per country. As expected, as the app promotion took place in Egypt on a large scale, Egypt is ranked number 1 for app installs. Surprisingly, as shown in the figure, the majority (7) of countries are Arab speaking countries.



English (United States)	159	27.85%
Arabic (United Arab E...	106	18.56%
English (United King...	90	15.76%
Arabic (Egypt)	61	10.68%
French (France)	61	10.68%
Spanish (United States)	23	4.03%
Spanish (Spain)	20	3.50%
English (Australia)	4	0.70%
Italian (Italy)	4	0.70%
English (South Africa)	3	0.53%
Others	40	7.01%

Figure 6.4: App Usage - Top 10 Display Languages

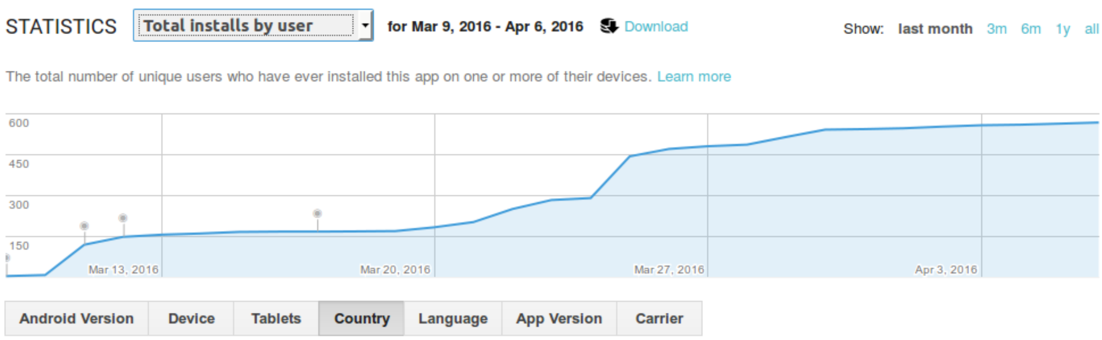


Figure 6.5: Total App Installs over Time

As any new Android application, the acquisition of new users is a very challenging process especially we are not investing much money on the marketing. Fig. 6.7 shows the daily installs for Slangsh over time. As shown in the figure, there are some peaks. We already mentioned in Section 6.5.1 about exceptional events that helped as promoting the app on March 11th as well as on March 25th. The increasing rate from March 20th to 24th as well as from March 29th to April

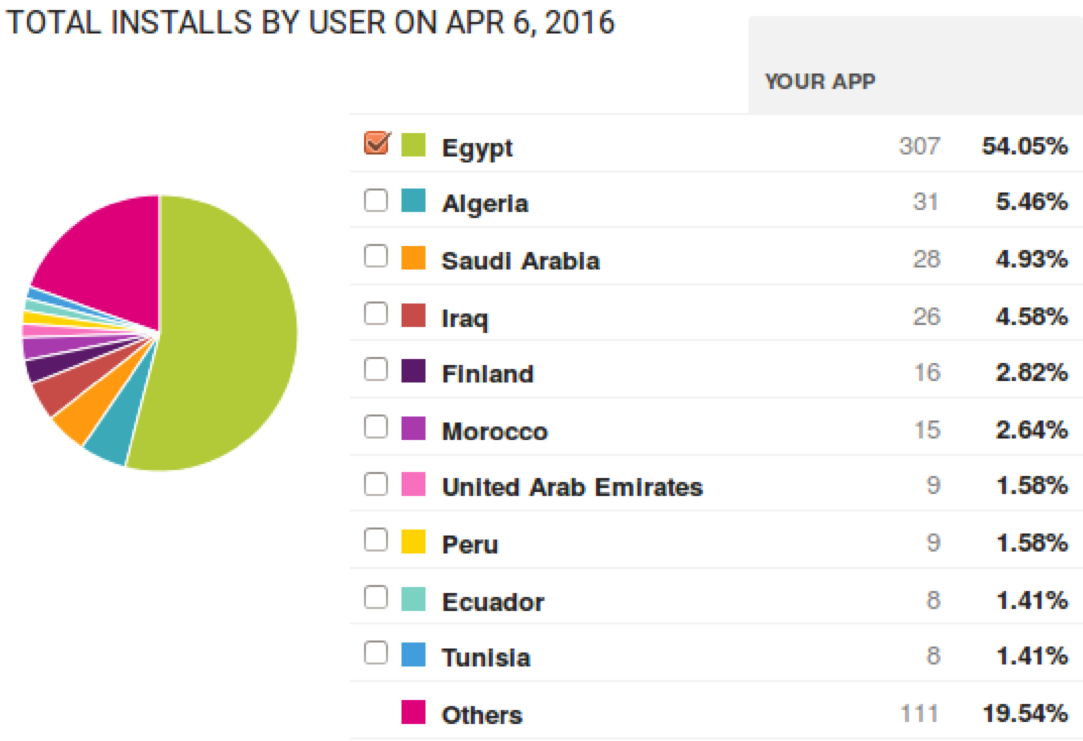


Figure 6.6: Total App Installs per Country

1st was due to marketing campaigns using Google Adwords.

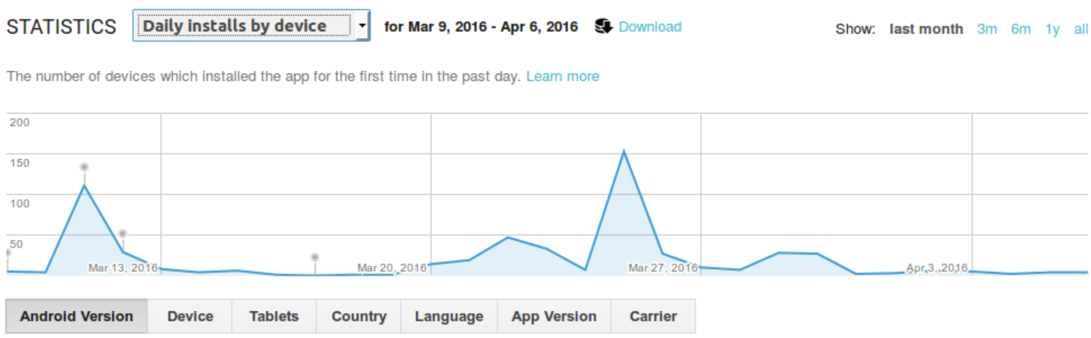


Figure 6.7: Daily Installs over Time

More than expected, the total number of uninstalls (i.e., users removing the app from their smartphone) is quite high. Fig. 6.8 shows the daily uninstalls for

Slangsh over time. Unfortunately, the current number of installs is 235 which means that more than 50% of users have already uninstalled the app. Fig. 6.9 shows the current number of installs per country. As shown in the figure, the peaks for uninstallations happen in the same time as the peak of installations. Uninstallation is common for new apps especially if the content is not rich enough. However, there are some other reasons that might have discouraged the users from using the app and unistall it. We are going to discuss these reasons in more details in Section 6.6 that is about current challenges and limitations.

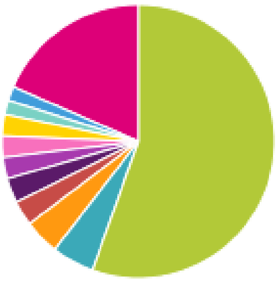
Figure 6.8: Daily Uninstalls over Time

6.5.4 User Activity

In Slangsh app, we track users' activity by monitoring the number of times each user visited the "Home Screen". This is the main screen in the app from which user can make any navigation and actions inside the app. Additionally, we also track the amount of time each user is spending on the app during specific session (i.e., unique time to open and use the app). Fig. 6.10 shows the number of users who are active on the app over time. As shown in the figure, these users could be returning users, or new users where the returning users are the users who already installed the app and open it from time to another. Apparently, the percentage of returning users are higher than the new users. We are currently motivating the users to open the app from time to another using "Push Notifications" that is a notification that reminds the user every two days to share something on the app.

As shown in the figure, activity of the users is proportional with the daily number of installs as shown in the previous Section 6.5.3. The figure also shows that the average time spent per user's session is around 7 minutes which is very good and means that users like the app and each user is spending enough time trying the app and its features. Fig. 6.11 shows the average session duration considering time spent in different sessions by all users in specific day.

CURRENT INSTALLS BY DEVICE ON APR 6, 2016



	YOUR APP	
Egypt	132	55.46%
Finland	12	5.04%
Saudi Arabia	10	4.20%
Algeria	7	2.94%
Iraq	7	2.94%
United Arab Emirates	6	2.52%
Morocco	6	2.52%
Peru	6	2.52%
Ecuador	4	1.68%
United States	4	1.68%
Others	44	18.49%

Figure 6.9: Current Installs per Country

6.5.5 User Behaviour

In order to validate the proposed features and design decisions of our proposed solution, it was very important to track users' behaviour on the app and know exactly what they are doing. Accordingly, we monitor every action the user is doing inside the application. Fig. 6.12 gives an overview about the total number of events (i.e., actions) happened by different users over time. As shown in the figure, the total number of event during the last 4 weeks is 2509 which shows that users are engaged and interacting with different features in the app. The figure shows that the average number of actions per user session is 4.9 which means that each user is doing on average 5 actions on the app.

To get a more narrower view on which actions users are mostly interested in and more attracted to, Fig. 6.13 and Fig. 6.14 show a full list of actions (17) available inside the app ranked based on current users' behaviour. From these statistics and if we consider the top 10 actions performed by the users, we can get very useful insights and implications. First, the statistics show that users care about the quality of content. The top action performed by the users is "voting down

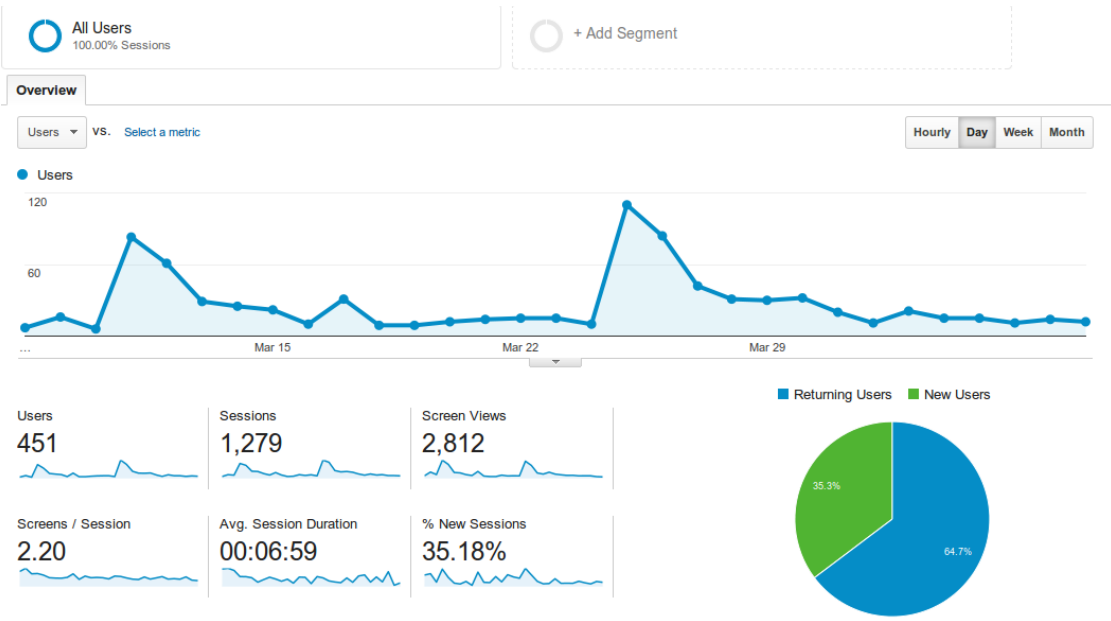


Figure 6.10: Active Users over Time

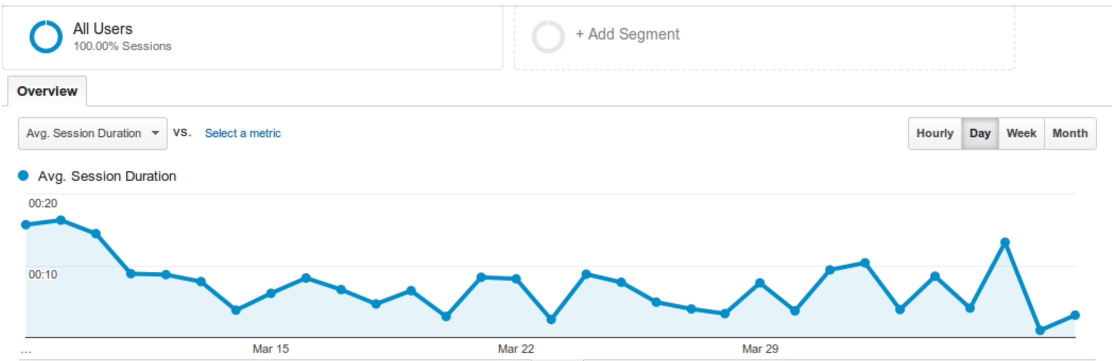


Figure 6.11: Average Session Duration

slang" where "voting up slang" action ranked 4th in the list. These actions are being used to state whether the word or idiom posted by other users are slangs or not. This is also expected as these actions are very simple, usable and just requires the user to press a button while scrolling the slang feed. Second, users mostly are either not familiar with the definition language of slangs, or would like to check slang definition in more than one language. The action "Check Translation of Slang Definition" as ranked as the 2nd most used action by the users. Third, users

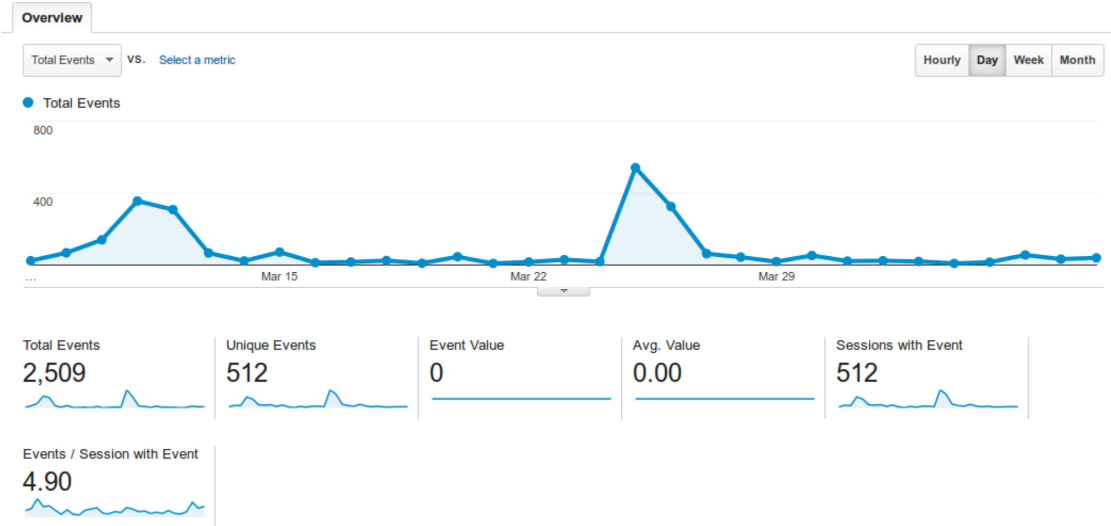


Figure 6.12: Total Number of Actions over Time

care about incentives (both intrinsic and extrinsic) as we discussed in Chapter 4. For the intrinsic motivations, as shown in the statistics, the third most used action is "Guess this Slang" which shows that users are spending time not only to browse slangs, but also to have fun in the "Play Tab" (Fig. 4.9). In addition, action "Dare Friends" is ranked as 6th that is being used by the users to share a question about specific slang with their friends on different social media channels. Then, their friends should guess this slang. Moreover, action "Check Answer for Slang" is ranked number 10 which is used by the users if they could not guess the correct slang word or idiom and want to check the answer. On the other hand, for the extrinsic motivation, users are using the action "Check my Credit" which shows specific credit based on user activity in the app and this action is ranked 8th. Finally, regarding slang sharing, the statistics show that users use different flows in the app to share slangs. Either the users are self motivated to share the slang (action ranked 5th - "post new slang"), or users are motivated by the welcome message (action ranked 7th) that tells the user that they will get extra points when they share a new slang. It is worth mentioning that starting the action to post a new slang will always be completed to the end. We will discuss that in more details in Section 6.6.

If we consider the actions ranked between 11 to 17, we will find that users currently are not using the "report slang" feature that much. Based on our observations, all of the slangs that have been shared are appropriate and only few inappropriate slangs have been reported by the users and we manually removed them from the system. Finally, the feature "Add new Translation" is not used much by the users and is almost ranked last (15th) among all actions. This feature allows the users to translate the slang definition into other languages. We are going to discuss possible reasons for this behaviour in Section 6.6.

Event Action	Total Events ↓	Unique Events
	2,509 % of Total: 100.00% (2,509)	512 % of Total: 40.03% (1,279)
1. VoteDownSlang	629 (25.07%)	222 (17.58%)
2. CheckTranslationFeed	483 (19.25%)	201 (15.91%)
3. GuessThisSlang	310 (12.36%)	98 (7.76%)
4. VoteUpSlang	252 (10.04%)	107 (8.47%)
5. PostNewSlang	190 (7.57%)	140 (11.08%)
6. DareFriends	130 (5.18%)	75 (5.94%)
7. ShareByMotivation	106 (4.22%)	106 (8.39%)
8. CheckMyCredit	102 (4.07%)	82 (6.49%)
9. CheckTranslationsPlay	79 (3.15%)	48 (3.80%)
10. CheckAnswerSlang	64 (2.55%)	34 (2.69%)

Figure 6.13: Top Actions Performed by the Users - 1 to 10

6.5.6 Statistics of Slangs

We mentioned that we pre-populated some slangs (55) manually before publicly releasing the Android app. Currently, we have 182 slangs on the app. This means that users have shared 127 native slangs. The majority of these slangs is Arabic from Egypt. This makes sense as we have stated in the statistics that the majority of people installed the app are from Egypt. Fig. 6.15 shows statistics of slangs shared by users in different languages.

Fig. 6.15 also states that the available slangs are from 9 different languages. However, these slangs have been shared by users from 20 different countries. The reason for that is there are some countries speak the same language (e.g., Mexico,

Event Action	Total Events	Unique Events
	2,509 % of Total: 100.00% (2,509)	512 % of Total: 40.03% (1,279)
11. ShareByMotivationDescribtion	46 (1.83%)	46 (3.64%)
12. TellFriend	27 (1.08%)	25 (1.98%)
13. ReportSlangFeed	25 (1.00%)	22 (1.74%)
14. RateSlangshMySelf	22 (0.88%)	17 (1.35%)
15. AddNewTransaltion	15 (0.60%)	12 (0.95%)
16. DisableDailyNotification	15 (0.60%)	14 (1.11%)
17. ShareSlangFeed	14 (0.56%)	14 (1.11%)

Figure 6.14: Top Actions Performed by the Users - 11 to 17

Result Grid Filter Rows: Export: Wrap Cell Content:

#	name	count(*)
1	Arabic	124
2	Spanish	27
3	English	21
4	Portuguese	3
5	French	2
6	Hindi	2
7	German	1
8	Dutch	1
9	Romanian	1

Figure 6.15: Slang Statistics - Grouped by Language

Spain, Colombia). Fig. 6.16 presents statistics of slangs shared by users in different countries.

Result Grid Filter Rows: Export: Wrap Cell Content:

#	name	count(*)
1	Egypt	119
2	Spain	20
3	Ireland	8
4	United States of America	7
5	United Kingdom	4
6	Iraq	3
7	Mexico	3
8	Portugal	3
9	Dominican Republic	2
10	France	2
11	India	2
12	United Arab Emirates	1
13	American Samoa	1
14	Bahrain	1
15	Bolivia	1
16	Canada	1
17	Colombia	1
18	Germany	1
19	Netherlands	1
20	Romania	1

Figure 6.16: Slang Statistics - Grouped by Country

We also measured some statistics related to the number of sentiments, domains, age-ranges, and translations attached to available slangs. First, the average number of sentiments attached to each slang is 2.3. Second, the average number of domains (i.e., contexts) attached to each slang is 4.9. Third, the average number of age ranges attached to each slang is 2.5. Forth, the average number of definition translation attached to each slang is 1.2. These statistics show that users spend reasonable time to attach sentiments, domains, and age ranges to each slang. However, the statistics show that users each slang only have the basic definition in one language. Fig. 6.17 shows the average of number different attributes attached to a slang. Finally, we think that the reason for high average of domains per slang is because in the User Interface design, we enable the user to select "All" domains if she feels that this slang could be used anywhere. This feature is not available with other attributes such as sentiment or age range where the user needs to choose them one by one

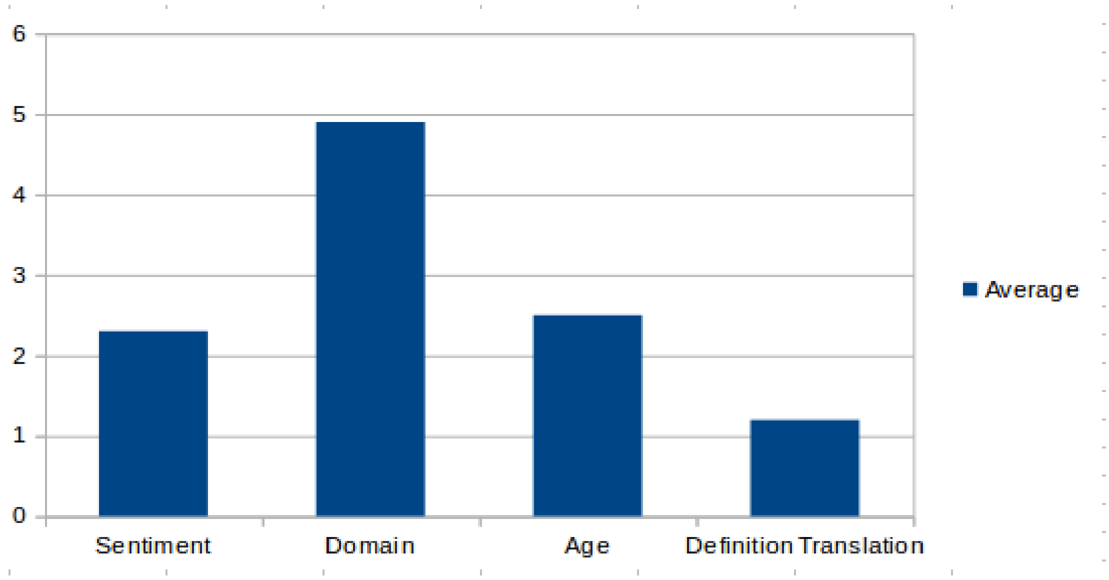


Figure 6.17: Slang Statistics - Average Number of Slang Attributes

6.5.7 Accuracy of Translation with Slangsh

One of our motives to develop Slangsh was to solve the problem of inaccurate translations of slangs using online translation services. In order to validate if Slangsh will have the potential to solve this problem, we selected 2 random Arabic slangs shared by users (mainly from Egypt). Then, by using Google Translate[11], first we tried first to translate the main slang text to English. Second, we compare the translation obtained by Google Translate with either slang's definition directly (if it is available in English), or the English translation of the slang definition. The ground truth is based on our knowledge as the Arabic (Egyptian) is the native language of one of the authors of this thesis.

[11] translate.google.com

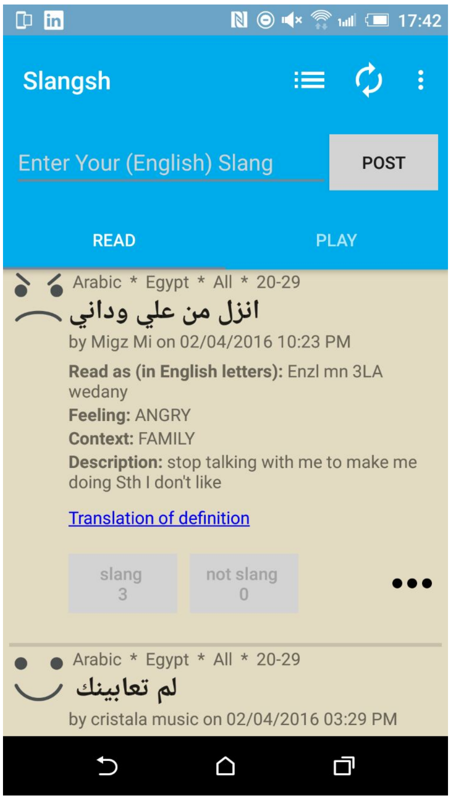


Figure 6.18: Arabic Slang- Sample 1

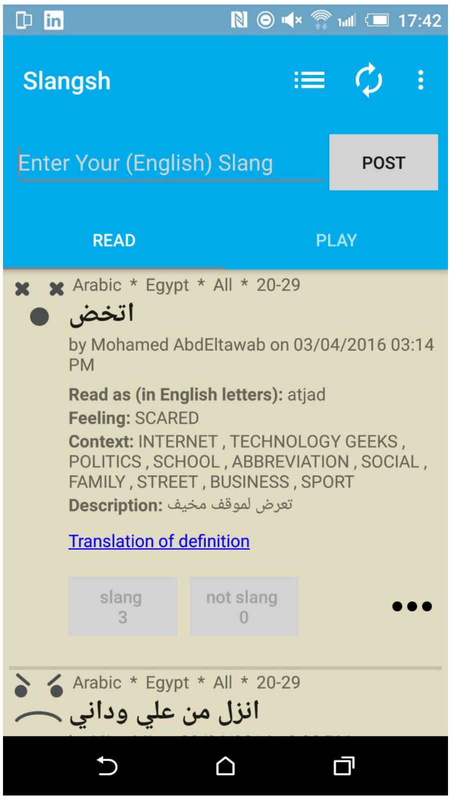


Figure 6.19: Arabic Slang- Sample 2

Fig. 6.18 shows the first slang sample. For this slang, the user has provided English definition which is "stop talking to me to make me do something i dont like". We used Google Translate to translate the main slang text. Fig. 6.20 shows the wrong result we got from Google translate. The translation we got is "Get off of Ali and Danny". This means that Google Translate thought that some words of the slang text are names of people which is not true. Moreover, the whole translation is totally wrong. Fig. 6.19 shows the second slang sample. We first translated the slang text using Google Translate. Fig. 6.21 shows the result of Goolge Translate which is totally wrong. What Google Translate actually did in this case was to map the Arabic letters to its corresponding English letters (i.e., in pronunciation) which is totally wrong. After that, we tried to translate the given Arabic definition for the slang. Fig. 6.22 shows the translation we got from Google Translate which is the right translation for the word as mentioned by the used. In addition, this could be validated more by comparing the word "scary" in the translation text with the slang's main sentiment.

Figure 6.20: Wrong translation from Google Translate for Arabic Slang- Sample 1

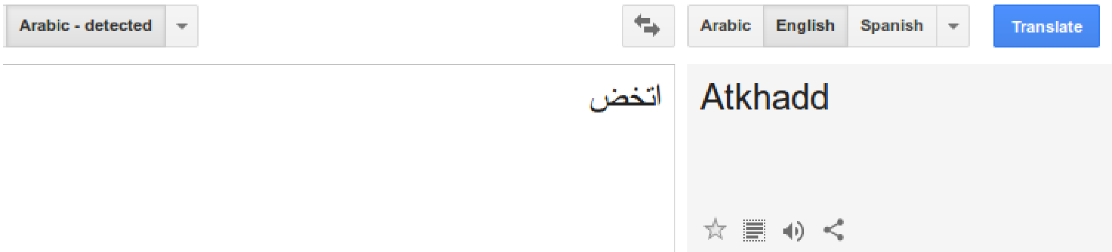


Figure 6.21: Wrong translation from Google Translate for Arabic Slang- Sample 2

Figure 6.22: Correct translation from Google Translate for Arabic Slang Based on Slang's Definition Text- Sample 2

Our evaluation to the accuracy of slang translation shows a great potential for Slangsh to solve the current problem of inaccurate translation of slangs using online translate services such as Google Translate.

6.5.8 Ratings and Reviews

We got very good ratings and reviews from different users who installed and tried the app during the past 4 weeks (March, 11th to April, 8th). Slangsh's current rating on Google Play Store is around 4.8 which is relatively very high. Fig. 6.23 shows the current rating of Slangsh on Google Play Store. The majority of users (29 out of 34) marked Slangsh as a 5 stars app.

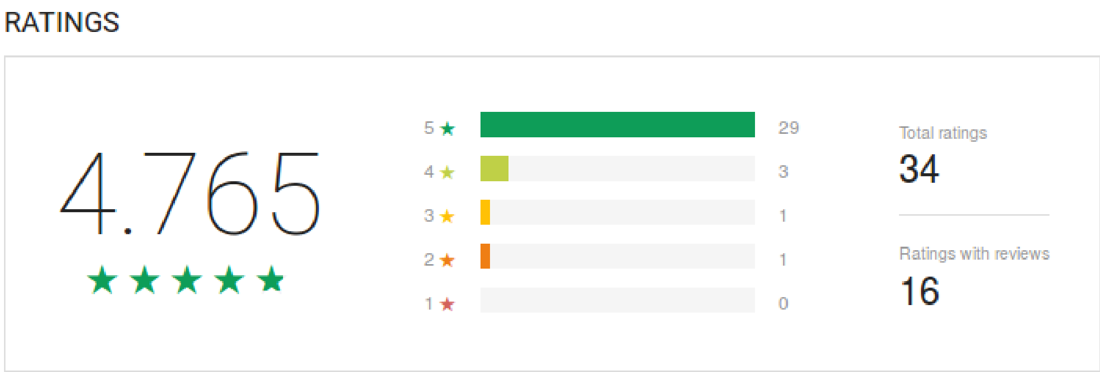


Figure 6.23: Slangsh Ratings - Google Play Store

6.6 Challenges, Limitations, and Future Work

In this chapter, we have evaluated and analyzed different aspects in Slangsh. Based on this evaluation, we identified some challenges. In this section, we are going to discuss these challenges.

The first main challenge is to promote Slangsh's Android app so that many users could download and use it. However, we are currently restricted by specific budget that prevents us from doing marketing on a large scale. Second, we have a problem to retain users who already installed the app as more than 50% has uninstalled the app. Based on our analysis to this issue, there are some possible reasons. The first reason is that there is no enough content on the app that makes the users satisfied. The second possible reason is that the current set of incentives are not motivating enough for the users. The third reason that is based on direct feedback from some users is that the app is not very usable. Finally, the fourth and very important reason is that the users care so much about their privacy. We found out that 167 users has downloaded the app, but not registered at all. This means that they have uninstalled the app even without trying it. The clear reason is that we ask the users to login and register by their Google Account (this is called Social Login). The purpose of this step is to get the user's accurate email address. However, it seems that many users do not prefer to log in with their Google Account especially the app is new and not well-known.

Third challenge is related to the number of current registered users (390) compared with the number of shared slangs (127). We found out that users download, use the app, and try different features inside it. However, they do not share their native slang. This suggests that we have a limitation with the offered incentives as well as the usability of the app. Fourth, and possible for the same reason, users are not motivated to collaborate and add translations to slangs' definitions. Another challenge related to the usability is that users sometimes choose wrong definition language that does not match the slang's definition text that they write. Finally, based on Google Analytics, we found that users might start the "share new slang" flow, but do not complete it to the end. This suggests that we might be asking for many details that discourage the users from sharing their native slangs, because they are lazy to input different information.

These challenges suggests that we have some limitations in the development of Slangsh. We are going to work on these limitations in the future. Accordingly, we can summarize our future work as follows:

- Improving the usability of Slangsh Android app.
- Add more incentives that encourage the users to be more engaged in the app.
- Develop a strategy to retain users after they install the app.
- Develop a new approach that make the users register to the app without worrying about their privacy.
- Promote and market for the app on a large scale.

Chapter 7

Discussion and Conclusion

In this thesis, we designed, developed, and proposed an Android application called "Slangsh". Our motivation was to propose a solution based on crowdsourcing and collaborative learning to enable us (in the future) to build the largest online knowledge base of worldwide slangs (i.e., slangs being used in different languages and countries) labelled with some information such as language, country, city, age, definitions, sentiments, and contexts. To our best knowledge, there is no any comprehensive online dictionary for slangs that could provide all these information. We validated our assumptions and different facts we collected about slang development in different languages using interviews and an online survey. In addition, we evaluated our solution by analyzing different users and usage statistics. In this chapter, we are going to discuss our main motivational goals, outcomes, as well as a conclusion of challenges and future work.

Our first goal was to propose a solution that would help people to learn slangs in different languages. In order to achieve that, we designed the Android application so that it enables users (i.e., people using the application) to do different actions with two different roles. First, users are able to share their native slangs so that other people can learn about these slangs. Second, users are able to browse the application and learn slangs shared by others. In addition, they are able to filter slangs in specific language. Currently, we only focus on three languages: Arabic, English, and Spanish. We discovered, within one month, that active users are spending on average seven minutes per app visit (i.e., when downloading the app for the first time, or returning back to the app at a later time). This shows that users spent reasonable amount of time to try different features in the app taking in consideration that the app is still new and the available content is not reach. We also found out that users performed around 2500 total actions in one month with an average of 5 actions per user's session. Based on our analysis to users' actions on the app, we were able to learn about what users like the most. For instance, users care so much about the quality of the content. They spent some time to vote up/down every content to approve whether this content is really a slang word/idiom or just a normal word/idiom. In addition, users usually wanted to check if there is any available translations for the definition of specific slang. Finally, by comparing the number of the users in our database with the number of current available slangs, we found out that around 40% of the users shared their own native slangs.

The second goal was to help online businesses to understand the semantics of text being exchanged on their platforms (slang texts in specific). In order to achieve this goal, we designed the android app so that when the user wants to share her own native slang, she will be able to attach some mandatory information with this slang such as age, sentiments, and contexts. Based on the analysis of current available slangs in our database, we found out that each slang is attached on average by 2.5 different age ranges. In addition, each slang is labelled with 2.3 sentiments on average and 4.9 different contexts. These statistics show that the users spent reasonable time to attach these information to the slangs they share. Especially we only require, in our design, to choose at least one item for each required information such as age, sentiments, and contexts. We found out "Slangsh" could have a good potential to provide some important semantics about slangs in different languages. Accordingly, this will be useful for online businesses if they want to make analysis on the textual data being exchanged on their platforms. However, the knowledge base of slangs data should be large enough to achieve this goal and this will require some time.

Our third goal was to address the problem of inaccurate translation of slang that is currently being faced even on popular translation services such as Google Translate[1]. Our approach to target this issue was to design our solution so that users provide at least one definition on slang in specific language. Additionally, the user can provide a translation for the definition when sharing it, or other users could provide different translations later. Based on our analysis, we found out that the average number of slang's definition translation is 1.3. This means that there is around one definition for each slang in specific language. However, we were able to validate our concept against Google Translate. First, we tried to translate the slang text using Google Translate. We got wrong translation using only the slang text for all samples we have chosen from the available slangs in our database. We used the available definition and our knowledge as a ground truth. Then, we tried to translate the available definition to English and compare this translation with the attached sentiment of the slang. Our results showed that "Slangsh" could have a great potential to solve the problem of inaccurate translation of slangs in different languages. In addition, we found out that the majority of users actually use formal language when they provide a definition to their native slangs and this

[1] https://translate.google.com

helps to obtain more accurate translations.

The fourth goal was to design our solution to be based on collaborative learning and crowdsourcing. Accordingly, when we were designing our solution, we thought about different incentives that would motivate the users to share their native slangs as well as to spend enough time using the app. Therefore, we used different type of incentives: intrinsic and extrinsic. First, we dedicated one part of the app for gamification, so that the users can have fun and enjoy using the app. Second, we designed the app so that the user get credits as long as they are sharing their own native slangs, adding a translation to an existing slang, or from playing on the app. We discovered that users actually care about these incentives. Based on our analysis, some of the top used actions were on the gamification module of the app and includes: guess slang, challenge friends, check answer, and check credits. These statistics show that incentives is an important design factor in the proposed solution.

Finally, we can conclude this thesis with current challenges and future work. Based on our analysis and evaluation, we found out that we have some issues related to the usability of the app as well as the crowdsourcing incentives. First, we discovered that some people are downloading the application, try different features, but they do not share any slang. We concluded that by comparing the actual number of registered users with the actual number of the available slangs. Second, we have a drop out of the number of the users as more than 50% of the users already removed the application from their smartphones. This shows that we need to work more on the usability as well as the crowdsourcing incentives. However, we know that this behaviour should be expected as the application is new and the content available is not rich enough. In addition, we concluded that some users have a privacy concern as a big number of the users (around 30% of total downloads) downloaded the application, but have not registered. The main reason for this issue is that we require users to login with their Google account (this is called Social Login). Finally, one of the current main challenges is to get more users to download the app as the cost of promotion and marketing is high and our budget is currently limited. These challenges show that we need to work more in the future on improving the usability as well as the crowdsourcing incentives to download, use the app, and share their native slangs.

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Appendix A

Interview Questions

The personal and online interview questions were as follows:

- What is your home country and city?
- What is your age?
- Do you have slangs in your country? Tell us more about that.
- Do you usually use slang in daily life?
- Do you use slangs for online communication (e.g. on social media)?
- If I am going to learn your language, will I learn slangs, or just standard words or phrases?

Appendix B

Survey Questions

The following pages include a transcript of the questions used for the online survey. We have used Google Forms [1] to build and analyze the online survey.

[1] https://www.google.com/forms/about/

Slang Development in Different Languages

Slang is a type of language consisting of words and phrases that are regarded as very informal, and are typically restricted to a particular context (e.g. street or social) or group of people (e.g. country or city).

* Required

1. **Do you have slangs (informal words/idioms) in your language/country?** *
   Mark only one oval.
   - YES
   - NO

2. **Do you usually use slangs in your daily life?** *
   Mark only one oval.
   - YES
   - NO

3. **Do you use slangs for online communication (e.g. for texting on whatsapp, or any social media)?** *
   Mark only one oval.
   - YES
   - NO

4. **How often do you use slangs in your daily life/online communication?** *
   Mark only one oval.
   - 0 to 25 % of my time.
   - 25 to 50 % of my time.
   - 50 to 75 % of my time.
   - 75 to 100% of my time.

5. **Are slangs same in all cities in your country?** *
   Mark only one oval.
   - YES, all cities use the same slangs
   - NO, different cities use different slangs

6. **Are slangs different based on the age in your country (e.g. old people use different slang than young people)?** *
   Mark only one oval.
   - YES, different ages use different slangs
   - NO, all ages use the same slangs

7. **If there is another country speaks your language, would you be familiar with any slang from this country? (e.g. Mexico and Spain speak Spanish)** *

Mark only one oval.

- YES
- NO
- NOT SURE

8. **When you learn a new language (e.g. attend classes, watch online videos, use mobile/web apps), do you learn about the slangs in this language, or they just teach you basic, standard, and formal words/idioms?** *

Mark only one oval.

- Only Basic Words/Idioms
- Both Basic and Slang Words/Idioms

9. **Do you face any problem to get accurate translations for slang using online translators (e.g. Google Translate)?** *

Mark only one oval.

- YES, transaltions of slangs are always in-accurate.
- NO, transaltions of slangs are always accurate.
- SOMETIMES, transaltions of slangs are sometimes in-accurate.
- NEVER tried to translate a slang

10. **Would you be interested to learn about slangs in specific language(s)?** *

Mark only one oval.

- YES
- NO

11. **If yes, would you please list the languages?**

12. **What is your home country/native language? (e.g. United States/English)** *

13. **(Optional)Would you be interested to know about the results of this survey? Please write your email.**

Appendix C

Survey - Respondents' Information

This appendix lists the information related respondents' home countries and native languages. This information is listed as (home country/native language) as follows (hint: we remove duplicate entries):
United States/English
Italy/Italian Egypt/Arabic
UK/English
Australia/English
Bangladesh/Bangla
Serbia/Serbian
Finland/Swedish
Norway/Norwegian
Germany/German
Mexico/Spanish
Canada, English/French (bilingual)
New Zealand/English + Afrikaans
Sweden/Swedish
Palestine/Arabic
Ireland/English
Greek/Greece
Korea rep/Korean
Brazil / Portuguese
The Netherlands/Dutch
Maroco /Arabic
Slovenia/Slovenian
Canada/Spanish, French
Ukraine/Ukrainian
Poland/POLISH
France/French

China/ Mandarin
Malta/Maltese
Scotland/Scottish Gaelic
India/Kannada

Appendix D

Evaluation - Demographic and Context Information

The following figures show some statistics about full countries' list, the top 10 cities from which Slangsh is mostly used, as well as the top 10 deviced on which Slangsh is being installed and being used by users from different countries.

	Country	Sessions	Screen Views	Screens / Session	Avg. Session Duration
		1,279 % of Total: 100.00% (1,279)	2,812 % of Total: 100.00% (2,812)	2.20 Avg for View: 2.20 (0.00%)	00:06:59 Avg for View: 00:06:59 (0.00%)
1.	Egypt	674 (52.70%)	1,257 (44.70%)	1.86	00:04:02
2.	Finland	373 (29.16%)	1,163 (41.36%)	3.12	00:14:49
3.	Saudi Arabia	44 (3.44%)	79 (2.81%)	1.80	00:03:56
4.	United States	27 (2.11%)	49 (1.74%)	1.81	00:02:36
5.	United Arab Emirates	18 (1.41%)	33 (1.17%)	1.83	00:01:52
6.	Iraq	12 (0.94%)	21 (0.75%)	1.75	00:02:39
7.	Kuwait	11 (0.86%)	19 (0.68%)	1.73	00:05:01
8.	Germany	10 (0.78%)	22 (0.78%)	2.20	00:02:55
9.	Portugal	10 (0.78%)	15 (0.53%)	1.50	00:04:04
10.	France	9 (0.70%)	20 (0.71%)	2.22	00:02:32

Show rows: 10 Go to: 1 1 - 10 of 37

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Figure D.1: App Downloads and Usage - Top 10 Countries

Country	Sessions	Screen Views	Screens / Session	Avg. Session Duration
	1,283 % of Total: 100.00% (1,283)	2,794 % of Total: 100.00% (2,794)	2.18 Avg for View: 2.18 (0.00%)	00:06:50 Avg for View: 00:06:50 (0.00%)
11. Peru	8 (0.62%)	15 (0.54%)	1.88	00:04:25
12. Colombia	7 (0.55%)	12 (0.43%)	1.71	00:02:11
13. Algeria	7 (0.55%)	13 (0.47%)	1.86	00:06:53
14. Dominican Republic	6 (0.47%)	8 (0.29%)	1.33	00:01:24
15. Ecuador	6 (0.47%)	9 (0.32%)	1.50	00:01:00
16. United Kingdom	5 (0.39%)	1 (0.04%)	0.20	00:00:00
17. Nicaragua	5 (0.39%)	11 (0.39%)	2.20	00:05:33
18. Tunisia	5 (0.39%)	9 (0.32%)	1.80	00:00:29
19. Bahrain	4 (0.31%)	4 (0.14%)	1.00	00:01:05
20. Angola	3 (0.23%)	3 (0.11%)	1.00	00:01:13

Show rows: 10 Go to: 11 11 - 20 of 37

Figure D.2: App Downloads and Usage - Countries Ranked 11-20

Country	Sessions	Screen Views	Screens / Session	Avg. Session Duration
	1,283 % of Total: 100.00% (1,283)	2,794 % of Total: 100.00% (2,794)	2.18 Avg for View: 2.18 (0.00%)	00:06:50 Avg for View: 00:06:50 (0.00%)
21. Indonesia	3 (0.23%)	4 (0.14%)	1.33	00:04:34
22. Iran	3 (0.23%)	5 (0.18%)	1.67	00:01:28
23. Libya	3 (0.23%)	5 (0.18%)	1.67	00:00:35
24. Morocco	3 (0.23%)	3 (0.11%)	1.00	00:00:07
25. Netherlands	3 (0.23%)	3 (0.11%)	1.00	00:00:14
26. Philippines	3 (0.23%)	3 (0.11%)	1.00	00:00:32
27. Sudan	3 (0.23%)	7 (0.25%)	2.33	00:00:38
28. Venezuela	3 (0.23%)	6 (0.21%)	2.00	00:09:17
29. Spain	2 (0.16%)	5 (0.18%)	2.50	00:03:14
30. Oman	2 (0.16%)	3 (0.11%)	1.50	00:01:12

Show rows: 10 Go to: 21 21 - 30 of 37

Figure D.3: App Downloads and Usage - Countries Ranked 21-30

	Country	Sessions	Screen Views	Screens / Session	Avg. Session Duration
		1,283 % of Total: 100.00% (1,283)	2,794 % of Total: 100.00% (2,794)	2.18 Avg for View: 2.18 (0.00%)	00:06:50 Avg for View: 00:06:50 (0.00%)
31.	Russia	2 (0.16%)	0 (0.00%)	0.00	00:00:00
32.	Burkina Faso	1 (0.08%)	1 (0.04%)	1.00	00:04:12
33.	Bolivia	1 (0.08%)	3 (0.11%)	3.00	00:04:24
34.	Switzerland	1 (0.08%)	0 (0.00%)	0.00	00:00:00
35.	Guyana	1 (0.08%)	0 (0.00%)	0.00	00:00:00
36.	Malaysia	1 (0.08%)	1 (0.04%)	1.00	00:00:00
37.	Serbia	1 (0.08%)	2 (0.07%)	2.00	00:01:32

Show rows: 10 Go to: 31 31 - 37 of 37

Figure D.4: App Downloads and Usage - Countries Ranked 31-37

	City	Sessions	Screen Views	Screens / Session	Avg. Session Duration
		1,279 % of Total: 100.00% (1,279)	2,812 % of Total: 100.00% (2,812)	2.20 Avg for View: 2.20 (0.00%)	00:06:59 Avg for View: 00:06:59 (0.00%)
1.	Cairo	355 (27.76%)	631 (22.44%)	1.78	00:04:00
2.	Espoo	233 (18.22%)	817 (29.05%)	3.51	00:16:15
3.	Helsinki	140 (10.95%)	346 (12.30%)	2.47	00:12:26
4.	Giza	93 (7.27%)	208 (7.40%)	2.24	00:05:22
5.	Alexandria	57 (4.46%)	126 (4.48%)	2.21	00:04:33
6.	(not set)	47 (3.67%)	83 (2.95%)	1.77	00:03:13
7.	Tanta	43 (3.36%)	75 (2.67%)	1.74	00:03:33
8.	Zagazig	27 (2.11%)	53 (1.88%)	1.96	00:03:32
9.	Riyadh	23 (1.80%)	37 (1.32%)	1.61	00:02:17
10.	New Cairo City	14 (1.09%)	19 (0.68%)	1.36	00:00:29

Show rows: 10 Go to: 1 1 - 10 of 80

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Figure D.5: App Usage - Top 10 Cities

Mobile Device Branding	Sessions	Screen Views	Screens / Session	Avg. Session Duration
	1,266 % of Total: 98.98% (1,279)	2,812 % of Total: 100.00% (2,812)	2.22 Avg for View: 2.20 (1.03%)	00:07:03 Avg for View: 00:06:59 (1.03%)
1. Samsung	**471** (37.20%)	849 (30.19%)	1.80	00:03:27
2. HTC	**382** (30.17%)	1,145 (40.72%)	3.00	00:14:33
3. Huawei	**116** (9.16%)	215 (7.65%)	1.85	00:04:02
4. Sony	**97** (7.66%)	180 (6.40%)	1.86	00:04:01
5. Lenovo	**57** (4.50%)	150 (5.33%)	2.63	00:07:00
6. (not set)	**43** (3.40%)	71 (2.52%)	1.65	00:02:47
7. LG	**19** (1.50%)	36 (1.28%)	1.89	00:01:59
8. Infinix	**15** (1.18%)	21 (0.75%)	1.40	00:02:18
9. Archos	**11** (0.87%)	12 (0.43%)	1.09	00:00:44
10. OnePlus	**10** (0.79%)	30 (1.07%)	3.00	00:07:40

Show rows: 10 Go to: 1 1 - 10 of 25

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Figure D.6: App Usage - Top 10 Mobile Devices